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**Donald Trump's Pragmalinguistic Strategies in
Twitter Before and During the COVID-19 Crisis:
A Corpus-driven Approach**

MASTER'S DISSERTATION

Diogo César Henriques Jasmins

MASTER'S DEGREE IN LINGUISTICS: SOCIETIES AND CULTURES



UNIVERSIDADE da MADEIRA

A Nossa Universidade

www.uma.pt

November | 2021

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Master's dissertation in Linguistics: Societies and Cultures, supervised by Doctor Alcina Maria Pereira de Sousa (University of Madeira) and Doctor Anna Ivanova (University of O'Higgins), presented for public defence, at the University of Madeira, on the 16th of November 2021. The panel of examiners were the following:

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Doctor Alcina Maria Pereira de Sousa, Assistant Professor, University of Madeira (Portugal).

Dedication

To my grandmother, Maria Emília.

Acknowledgement

The conclusion of this dissertation was made possible thanks to the efforts of many people impossible to be named here. Thus, this research conveys not just my knowledge, learnt via research and true interest in the topic at hand, but also the knowledge of those who guided me, supported me and often gave me the motivation to continue working.

I would like to thank my supervisors Doctor Alcina Maria Pereira de Sousa and Doctor Anna Ivanova for raising and promoting an awareness of language that I did not have before and, most importantly, for their attentive guidance in my research through its several stages.

My gratitude is also addressed to both professors and colleagues with whom I have crossed paths in the two previous years. They have all been essential in building on my knowledge background, thus helping me to achieve my current goals.

Finally, I address my gratitude to my family and to those who hold a special spot in my heart, who have supported and motivated me to keep on working, particularly those who are no longer with us.

ABSTRACT

COVID-19 is one of the most remarkable worldwide crises of the latest decade with 33 million cases in the US as of the 1st of July 2021. In these difficult times citizens seem to have looked up to their leaders for guidance and support (Wood & Owens & Durham, 2005) as largely represented in the media (i.e., print press, online press and social media) whose study is nevertheless beyond the scope of full coverage and analysis in this dissertation. Rather interesting for this case study is the scrutiny of the way Donald Trump, the running President of the USA at the moment COVID-19 hit the country, interacted online and established the virtual rapport with interlocutors (Walther, 1992; Crystal, 2006; Greengard, 2009; Murthy, 2013; Baym, 2015 & Burgess & Baym, 2020) given his reported multiple ways of communicating globally with a focus on the COVID pandemic in the United States. The analysis of online Twitter corpora selected from Trump's Twitter in two periods (5 months prior and after COVID mentions in Trump's Twitter) makes it possible to look at the way Twitter messages were encoded, particularly evidenced in indexical expressions (i.e., personal pronoun reference) and the cooperative principle, both objects of scrutiny in this piece of research. More than the linguistic choices, or possible colligations and collocations to be associated with the lexeme COVID (via corpus linguistics and a discourse-based approach, following Baker, 2006; Biber, Conrad and Reppen, 1998; as well as corpus pragmatics, in the line of Romero-Trillo, 2017), this exploratory research study of interdisciplinary kind intends to disclose relevant pragmalinguistic strategies (Sousa & Ivanova, 2012) evidenced in tweet exchanges between a leading politician in the global scenario and internet users (Mirzaeian, 2020). This dissertation brings to the fore and discusses strategies likely to strengthen or deepen the gap among interlocutors.

Keywords: Twitter, Corpus Driven Approach, COVID-19, Pragmalinguistic Strategies, Donald Trump

RESUMO

O COVID-19 é uma das crises mundiais mais marcantes da última década, com 33 milhões de casos nos EUA a 1 de julho de 2021. Nestes tempos difíceis os cidadãos olham para os seus líderes à procura de orientação e apoio (Wood & Owens & Durham, 2005) como é amplamente representado nos *media* (ou seja, imprensa escrita ou *online* e redes sociais) cujo estudo está além do escopo e da análise desta dissertação. Interessante para este estudo de caso é o escrutínio da forma como, por exemplo, Donald Trump, o Presidente dos EUA no momento em que o *COVID-19* assolou o país, interagiu *online* e estabeleceu uma conexão virtual com os interlocutores (Walther, 1992; Crystal, 2006; Greengard, 2009; Murthy, 2013; Baym, 2015 & Burgess & Baym, 2020) devido às suas alegadas múltiplas formas de comunicar globalmente, tocando a pandemia *COVID* nos Estados Unidos. A análise de *corpora online* recolhido em dois períodos do Twitter de Trump (5 meses antes e depois do *COVID* ser mencionado no *Twitter* de Trump) torna possível observar como as mensagens são codificadas no *Twitter*, evidenciado em expressões indexicais (ou seja, a referência de pronome pessoal) e o princípio cooperativo, ambos objetos de escrutínio nesta pesquisa. Mais do que as escolhas linguísticas, ou possíveis coligações e associações a serem relacionadas com o lexema *COVID* (a partir da linguística de corpus e de uma abordagem baseada na análise do discurso, seguindo Baker, 2006; Biber, Conrad e Reppen, 1998; bem como a pragmática de corpus, na linha de Romero-Trillo, 2017), esta pesquisa exploratória de natureza interdisciplinar pretende divulgar estratégias pragmalinguísticas relevantes (Sousa & Ivanova 2012) evidenciadas em trocas de *tweets* entre um político prominente no cenário global e internautas seguidores (Mirzaeian, 2020). Esta dissertação ilustra e debate estratégias passíveis de promover ou aprofundar o distanciamento entre os interlocutores.

Palavras chave: *Twitter*, Abordagem Orientada por Corpus, COVID-19, Estratégias Pragmalinguísticas, Donald Trump

Epigraph

“When the pandemic hit, and changed the public’s priorities, populists across the political spectrum felt the need to come up with a new enemy to stay relevant and maintain public support. Many right-wing demagogues, from Bolsonaro in Brazil to Trump in the US, tried to present China as the new public enemy. Left-wing populists like Pablo Iglesias in Spain and Jean-Luc Melenchon in France, meanwhile, tried to blame the pandemic and the devastation it caused on the ideology of growth at all costs, especially at the expense of the environment. Neither side, however, managed to convince the majority of their supporters.” Available at <https://www.aljazeera.com/opinions/2021/6/25/beware-of-freedom-populism>, retrieved on the 13th of August 2021

List of Acronyms and Abbreviations

- API – Application Programming Interface
- CD – Compact Disc
- CMC – Computer-Mediated Communication
- COVID-19 – Coronavirus Disease 2019
- CP – Cooperative Principle
- EUA – Estados Unidos da América
- FTA – Face Threatening Acts
- FtF – Face to Face
- GC – Generalized Conversational Implicature
- GOARN – Global Outbreak Alert and Response Network
- ID – Identification/Identity/Identifier
- IM – Instant Messaging
- IRC – Internet Relay Chat
- MUDs – Multi-user Dungeons
- NBC – National Broadcasting Company
- SARS-COV-2 – Severe Acute Respiratory Syndrome Coronavirus 2
- SNS – Social Network Sites
- TV – Television
- U.S. – United States
- USA – United States of America
- W.H.O. – World Health Organization

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1. Introduction

The years 2020 and 2021 will be certainly recorded as times of the world pandemic due to the global spread of COVID-19. Amidst sickness, death, quarantines, country lockdowns and fear, politicians are expected to inform people as objectively as possible to mitigate citizen's unrest and anxiety facing a global pandemic. In this regard, the selection of appropriate pragmatic strategies underpins effective communication. The capability to adapt speeches, or messages in general, should be a valuable skill in a political figure's, Trump's, communicative toolbox since the president "is the most visible political and economic actor" (Wood & Owens & Durham, 2005:630) who has to be informative and reliable. The evaluation of the effectiveness of any communicative event is not a simple task, therefore it has caught the attention of several researchers in the field of linguistics, particularly those advocating the role of the cooperative principle (Grice, 1975) and most contemporary approaches in the field of pragmatics (*cf.* Leech, 1983; Fairclough, 1992, 2000, 2003, 2015; Horn, 1972, 2012; among many others).

Hence, following a corpus-based approach, it is important both to try and assume how the president's statements may be understood by national and international audiences and to understand the meaningful effects, positive or negative, of the president's rhetoric on audiences looking for guidance in a pandemic scenario. Populist leaders have been considered to use intentional discourse strategies and face threatening strategies, ending up igniting fear and low self-esteem among interlocutors¹, particularly at times of socio-political or economic unrest. These strategies are intended to manipulate and strengthen their authority and role as saviours, as advocated by Oliver and Rahn (2016), Savoy (2017), Appel (2018), Lacatus (2019) and Hidalgo-Tenorio & Benitez Castro (2021). This style of leadership creates fear among the citizens through the imagined threats which are claimed to take the form of real entities, people or the entire nation. (*cf.* Chapter 3.2. for evidence).

In order to understand a president's rhetoric and get a window into his/her hidden agenda, a citizen should be capable to deconstruct his/her statements, decoding how manipulative his/her "language play might be in a linguistic interaction" (Crystal, 2006). Political rhetoric in general, or populism in specific, can be somewhat understood through the

¹ In linguistics, particularly in the field of discourse analysis, an interlocutor (be it speakers or hearers) is "the person with whom one is engaged in conversation. The term implies a degree of interaction and reciprocity" (Swann, Deumert, Lillis & Mesthrie, 2004:150)

lens of nouns, adverbs and adjectives in use (*cf.* Chapter 5.1). The medium also affects the messages produced by the leaders, especially in the 21st century with a multiple range of online and offline platforms (Sousa & Ivanova, 2012; Sousa & Gouveia, 2021), which enable a number of possible ways for a president to reach his desired audience via virtual media and serve as a stage for a populist rhetoric (Rice-Oxley & Kalia, 2018).

The first president to venture in this new medium was reported to be Barack Obama. Although his press representatives and media team controlled all online posts (Ross & Caldwell, 2020), he was called the first internet president (Greengard, 2009). By contrast, President Donald Trump (Jan. 2017 – Jan. 2021) authored all his tweets, without resorting to any skilled professional help. Since Obama’s presidency (Jan. 2009 – Jan. 2017), and with a wider expansion of the Internet and its platforms, it became easier to create proximity with the public, seemingly more approachable and authentic, while synchronously – in real time – reaching wider audiences, both on national and international levels.

To this effect, advances Greengard (2009), Twitter has become the social media of choice for American politicians who look for all advantages when campaigning because Twitter has allowed² for a space where any piece of information can be said openly, ranging from beliefs (Murthy, 2013) to non-factual information or even lies. For instance, a president running for an office, could aim at being succinct and clear, navigating through the limitations of the virtual medium to make sure he/she is understood by audiences (Mancera & Pano, 2013). By contrast there could be instances of intended ambiguity meant to confuse audiences, which contribute to manipulation. It is thus relevant to understand the kind of rhetorical space created by Trump’s Twitter, following previous studies on Twitter communication of political figures like Barack Obama (*cf.* Sousa & Ivanova, 2012; Anderson, 2017; Ross & Caldwell, 2020; to name but a few). Yet, understanding the complex mechanisms behind language use in the media created by the Internet does require knowledge of the literature in the area of computer-mediated communication, albeit brief, following both its evolution through the last decade and several other studies done on the impact of social networks, like Facebook or Twitter, in political rhetoric (Anderson, 2017; Ott, 2017; Enli, 2017; Rice-Oxley & Kalia, 2017; among many others).

² The past is used since, as of 2021, Twitter does either censor or place warnings on tweets with misleading information.

1.1.Context

Before delving into a research study focused on Donald Trump's pragmalinguistic strategies, several contextualising issues contribute to a better understanding of the context of his communicative acts, departing from some of his personal notes, particularly rendered in this section, i.e., Donald Trump's short biography (one that is not self-authored) and some of the milestones on the evolution of the COVID 19 crisis, from its outbreak back on 1st of February 2021, as reported in the World Health Organization's website as well as in several news in online media. Lastly, it became relevant to establish the connection between the speaker/locutor and the context in which tweets were produced by addressing the role of political discourse in response to the crisis.

1.1.1. Donald Trump

To understand Trump in its time in office, one must first understand his social background alongside with some biographical data. Donald Trump has German roots from his great-grandparents who lived in Kallstadt, a village in Germany (Shapiro, 2016). In interviews Trump would often state that he was Swedish, a reported strategic lie that he picked up from his father, who lied about his origins to enjoy an easier time doing business with Jews who would otherwise distrust a German speaker/utterer (Shapiro, 2016). Donald Trump's grandfather escaped from home at 16 and migrated to America pursuing the gold fever. Once there he opened restaurants/brothels in several cities (Shapiro, 2016). During that time, he Americanised his family name, from Drumph to Trump and became a fully-fledged citizen. After having sold his businesses, he went back to Germany and got married, but was later expelled from the country, having been charged of avoiding military service (Shapiro, 2016). In America, Donald Trump's grandfather had a son, Trump's father, who died later of pneumonia during a nationwide flu epidemic (Shapiro, 2016).

Donald Trump's father, Fred Trump Jr., went into real estate business from a young age and later in life profited from the World War II conflict by building barracks and other buildings for the military, and even by planning buildings for returning vets (Shapiro, 2016). At the time, a report issued in the *New York Times* stated that he was arrested during a conflict and further insinuated that he was a member of the Ku Klux Klan (Shapiro, 2016). Fred Trump Jr.'s 4th child was Donald John Trump.

During his childhood, neighbours of the family considered Donald Trump "hyper-competitive, controlling and a bit of a neighborhood bully" (Shapiro, 2016:21). Neighbours

blamed his upbringing and claimed that his parents did nothing to correct his behaviour. The same happened at school, where teachers would not manage to control his attitudes, so as not to lose the valuable asset that his father was (Shapiro, 2016). After observing how their son was misbehaving and was only getting worse and worse, Trump's parents sent him out of school to a military academy where it was reported that he did not know how to take care of himself (Shapiro, 2016). During this time, it was often stated that he was physically violent with his colleagues, yet later, at university, his fellow students claimed he was unnoticed, and some did not even have the faintest idea of his existence there (Shapiro, 2016). While studying, Trump worked in the real estate business and got a loan of 2 million dollars from his father. He was awarded his bachelor's degree in Economics, even though his academic scores are unknown (Shapiro, 2016). During his first years in real estate business, Trump was accused of discrimination towards African Americans. In 1996 he started his partnership with NBC (Duignan, 2021).

Interestingly, Donald Trump claimed in the 1980s that he would run for president. Yet, he only ended up doing so in 2016. He was accused of deviating charity funds to his own campaign (Duignan, 2021). As of Jan. 2021, Donald Trump is no longer the president of the United States.

1.1.2. COVID-19

This section is meant to give a brief overview of the recorded history of COVID-19. It focuses mainly on the view rendered in the media in the United States. Information is gathered online from news media and from the official timeline of the website of the World Health Organization.

On the 31st of December 2019 a press release issued in Wuhan (China) mentioned cases of a viral pneumonia and, on the 2nd of January 2020, the World Health Organization (W.H.O.) informed the Global Outbreak Alert and Response Network (GOARN). On the 3rd of January 2020 Wuhan provides W.H.O. with information on the pneumonia which was first publicised to the media on the 5th of January. On the 11th of January the first death occurred in Wuhan and, on the 13th of the same month, the first COVID infection occurs outside China.

In the U.S., on the 20th of January, three airports started screening for SARS COVID-19 and a day later, on the 21st, the first case of COVID-19 was reported in the U.S. On the same day, W.H.O. confirmed that the virus could be transmitted from human-to-human. Wuhan was

object of lockdown on the 23rd of January. At this point and acknowledging the gravity of the disease, W.H.O. issued a global health emergency note followed by a global air travel restriction on the 2nd of February. On the following day, the 3rd, Trump's administration declares the state of public health emergency. Later, during the same month, on the 24th of February, team leaders of the W.H.O. in China confirmed that the world was not prepared for the restrictions needed to prevent the rapid spread of COVID-19. The virus continued to be disseminated globally and on the 11th of March W.H.O. declares COVID-19 a world pandemic.

In response to this official statement, Trump declared COVID-19 a national emergency and on the same day, the 13th of March, he issued a travel ban for all non-US citizens, because W.H.O. considered Europe the epicentre of the pandemic. On the 12th of May, medical officials stated that the death toll of 80.000 was a large underestimation of the scope of the pandemic; on the 20th of May, 100.000 deaths were reported. A few weeks later, on the 10th of June, there were 2 million known cases in the U.S.; a month later, on the 7th of July, there were 3 million known cases. On the 9th of July, W.H.O. informed that the virus could be airborne and the following month, on the 13th of August, presidential nominee Biden called for a 3-month mask mandate. Later on, the same month, the U.S. reported their case of reinfection.

On September 1st the Trump administration refused to join W.H.O.'s initiative for a vaccine implementation which could be equally distributed among poor and developed countries. The same month, on the 28th, the world reaches 1 million deaths. On the 2nd of October Trump tested positive for COVID-19 and got hospitalized. On the 19th of October, there were 40 million global cases of infection with the coronavirus. On the 4th of November the United States hit their milestone with 100.000 COVID-19 cases on a single day. Closing the year 2020, on the 31st of December, the U.S. fell short of its plan for 20 million vaccinations, distributing 14 million doses. Wang et al. (2021) reported that on the 1st of February there were more than 100 million global cases of COVID-19 and more than 2 million global deaths.

1.1.3. Political Discourse in Response to the Crisis

The main research problem of this study is to uncover and understand whether the pragmalinguistic strategies used by Donald Trump changed during the COVID-19 crisis (2019-2020), possibly aiming at being more informative and consistent, which is done by deconstructing his Twitter communicative strategies. This is important because one expects leaders to adapt their messages to an evolving crisis, updating information so as to be accurate

and reliable. This requires responsibility, clarity and playing safe, since presidential statements are more than ever spread online to a wider range of interlocutors. Getting to learn about the way the COVID-19 crisis has affected the world, thereby creating physical distancing (lockdowns), it is expected that audiences worldwide would go online looking for reliable information in the hope that leaders could provide timely guidance in difficult times, transmit their fact-based messages in an effective and responsible way, thereby mitigating misinformation. Being informative, in Gricean terms, should be a major focus in leaders' response during any crisis, yet this prerequisite (under scrutiny in Chapter 5.1.3) is not always successful. Furthermore COVID-19 has evolved into several variants, as reported by the W.H.O. While playing safe and relying on sound evidence, political leaders could have avoided serious outbreaks, public riots, not to mention enough time to have considered their choice of linguistic and extra-linguistic strategies when communicating in various modes (verbal and non-verbal communication in digital media) which are now mediatized instantly. Observing the months prior to Donald Trump's 2020 election, one could infer and foreshadow, the impact of a president's power to misinform his interlocutors (nationally and internationally), given his sarcasm and non-factual information, underpinning his response to citizens on the COVID-19 crisis. The information provided by a leader is expected to be in support of all interlocutors and unrest may arise when that is proven not to be the case (through an *Us-versus-Them* rhetoric as mentioned by Homolar & Scholz (2019), turning viruses into entities).

The crisis rhetoric is not limited to situations in which there is an actual global crisis. This rhetoric can also create a further feeling of crisis and chaos by spreading the idea of an imminent danger to the nation and citizens (Hidalgo-Tenorio & Benitez Castro, 2021). The use of lexemes like *crisis* or *scandal* is further perceived as a political weapon, which challenges citizens to follow the president's ideals blindly. The crisis scenario is believed to be the right context to trigger extreme and rapid change in society, benefitting some individuals over others (Lacatus, 2019). Trump's rhetoric polarized the American society, as he changed roles according to his whims mostly to fulfil his goals, sometimes under-evaluating the crisis and other times, unfortunately rather often, inculcating fear (Chernobrov, 2018) with a strong impact on citizens' response on a daily basis as reported in the media worldwide (both mainstream media and social networks).

2. Aims and Relevance

This section discusses the main aim of this study, the approach devised, along with the specific objectives of the research study. Furthermore, the relevance of the study is explained and the representativeness of the corpora is offered in detail, following Tognini-Bonelli (2001).

2.1. Aims of the Study

The main aim of this study is to account for changing pragmalinguistic strategies likely to be found in the Twitter communication by Donald Trump, by contrasting the language used before and during the COVID-19 crisis rather than looking into his political choices or information given in other media. This is so because it is important to understand if a global crisis impacts the rhetorical style of political leaders at large, in this instance the former leader of one of the most influential nations in the geopolitical realm.

A corpus-driven approach is meant to “drive linguistic categories systematically from the recurrent patterns and the frequency distributions that emerge from language in context” (Tognini-Bonelli, 2001:87). Therefore, no assumptions are made of Trump’s rhetoric, instead there is a commitment towards the data which is analysed objectively (Tognini-Bonelli, 2001). Interpreting how to account for Trump’s pragmalinguistic strategies in Twitter can be challenging, because these strategies may or may not come up to be unique to his political profile and character and as such a bottom-up approach makes the topic feasible. A bottom-up approach is possible thanks to the use of computational tools in this research such as Wordsmith Tools 8. The task of analysing pragmalinguistic strategies is further explored in the light of the conversational maxims by Grice (1975), i.e., through the careful analysis of utterances, followed by the analysis of tokens, collocates (Sinclair, 1991) and semantic prosody, up to the context of messages in Twitter.

The timeframe chosen for this study allows for several lines of analysis, because the data encapsulate a lot of information about Trump’s linguistic choices. Thus, it became pertinent to select specific objectives for this study. It is relevant (i) to take a corpus-driven approach, i.e., to look at “recurrent patterns and frequency distributions” (Tognini-Bonelli, 2001:84) to deconstruct Trump’s utterances, by scrutinising “previously defined linguistic constructs” (Biber, 2010:10), parts-of-speech, which allow for conclusions to be reached on pragmalinguistic strategies underlying a communicative style and its impact on interlocutors.

In the same scope, it is pertinent that subject pronouns are analysed separately, so as (ii) to look at indexical expressions (discourse deixis), mainly at the use of personal pronoun reference, to understand who the interlocutors are, as referred in Trump's Twitter, despite considering that in this medium (writing) shared knowledge is purely estimated and there is a certain degree of presupposition involved in interpreting messages (Ferenčík, 2004). Hence, as mentioned before, it is relevant from the pragmalinguistic framework (iii) to draw on the cooperative principle for the analysis of conversational implicature through (but not limited to) the analysis of information given around the topic of COVID-19 and through the analysis of vague expressions (lexical ambiguity).

2.2. Relevance

Considering the pandemic scenario on which this study is focused, figures in positions of power and leadership are supposed to be prepared to be challenged linguistically. In other words, speakers ought to be prepared to answer citizens' questions and, in communicative events, they would act based on truthfulness and factual information while, at the same time, being capable of change when new information arises (Austin, 1962). Considering that all citizens across contexts are being affected by the pandemic, which has affected several domains, such as health, economy, tourism, politics and many other sectors, it is relevant to interpret the way Donald Trump's messages were transmitted and the extent to which these could be (mis)interpreted by audiences. The approach to the topic of this study is thus important to understand the impact of political rhetoric in citizens' daily lives, which may be manipulated to spread false information unconsciously.³

The novelty of this study is in that it analyses Donald Trump's Twitter communication, yet contrasted in two different time periods: one of which is heavily impacted by a global disease which shifted the norms of the global context. Therefore, it is pertinent to understand how Donald Trump communicated in Twitter before and during the pandemic, so as to know if he was informative when discussing issues, producing utterances supposedly of factual content, or if his social media was an outlet for emotional outbursts without consideration of the possible consequences. This study also allows for the contrastive analysis between two periods which are expectedly different and may (or not) change the linguistic choices by Trump.

³ For instance, Trump telling citizens to try injecting disinfectant is highly dangerous and does not follow the information provided by health experts, as reported in the media on April 2020.

The issue often found with a corpus-driven approach is the representativeness of the corpora (Tognini-Bonelli, 2001). Because of this constraint, the corpora are collected to represent two very different time periods and their pivotal point is the first mention of coronavirus in Trump's Twitter. This study opted for 5 months per corpus (10 months on the whole; *cf.* Chapter 4) considering it as a measure that could represent effectively the rhetoric style of Trump, due to his continuous use of Twitter, as vastly disseminated in the media and in literature (*cf.* Chapter 3)

3. Literature Review

This chapter comprises the state of the art intended to cover briefly all topics that are relevant to fulfilling the aims of this study; its structure is introduced through a brief synthesis. First, it starts with an overview of computer-mediated communication, interestingly called by Davis & Brewer (1997) as electronic discourse. This section of the literature follows some foundational work on interpersonal interaction and its effects, laid down by Walther (1992, 1994 and 1996) as well as research on the sociopsychological aspects of computer-mediated communication discussed, for instance, by Kiesler, Siegel & McGuire (1984). The section refers then to several assumptions on new media, namely: Baym's (2015) analysis of the way people react to media and interact while using it; Gershon's (2017) interpretation of the newness of media; and Suchman's (1985) view of human-machine interaction. Concerning Twitter in particular, Murthy (2013) discusses the general linguistic structure and explains the several functionalities and limitations of this social network, through which users should learn how to communicate (Mancera & Pano, 2013). Anderson (2017) introduces research data which connects political rhetoric and Twitter communication by giving an account of the number of tweets made at the time of his research and states how many politicians had accounts in social networks. Moreover, research is done on fake news having spread in social media (Bovet & Makse, 2019; Anger & Kittl, 2011; Grinberg et al., 2019), and particularly on the power exerted by influencers in the spreading of the aforementioned fake news (Cuello-Garcia, Pérez-Gaxiola & Amelsvoort, 2020; van der Linden, Roozenbeek & Compton, 2020) and lastly on social media crisis management (Civelek, Çemberci & Eralp, 2016; Cinelli et al., 2020; Naeem and Bhatti, 2020).

Second, and focusing on political rhetoric, Windt (1986) and Zarefsky (2004) work on its definition and on outlining the power of a president, whereas Wood, Owens & Durham (2005) discuss the visibility of the president. Goffman (1983) states that people communicate

through rituals of language; Murphy (2009) analyses language as a means to comprehend the values of a politician. The research by Lakoff (1993), Lakoff & Johnson (2003) and Koller (2011) help to better understand metaphors used by politicians. Lacatus (2019) discusses populist rhetoric which according to Hidalgo-Tenorio & Benitez-Castro (2021) entails the style that better suits Donald Trump (*cf.* Chapter 3.2.). This is further supported by Appel (2018) and Oliver and Rahn (2016) who label Trump's style as Trumpenvolk during the 2016 elections. The 2016 electoral campaign is further scrutinised by Savoy (2017), who observed the rhetorical style of every candidate. Then, later on, Lacatus & Meibauer (2020) reached the conclusion that Trump changed the norms in politics; Homolar & Scholz (2019), in their turn, put forth the term Trump-speak, meaning a rhetoric that is emotionally charged and impacts the establishment directly (Lockhart, 2018). Some other scholars, like Sanchez (2018), connect Trump's rhetoric primarily addressing white supremacist groups while considering the speakers' use of textual winks; yet Kelly (2019) considered that his rhetorical style connects victimization to virtue.

In the range of political rhetoric, some research of interest for this dissertation might be considered, particularly, the one on crisis rhetoric, starting by an introduction to the topic by Wodak (2021) and Attila (2020), as well as Homolar & Scholz (2019) who comment on the division created between *Us* and *Them*. This division contributes to the debate, in the view by Hart & Tindall (2009), who consider the exploitation of crisis for personal benefit. This is also supported in Lacatus' (2019) argument in that the focus on the crisis benefits individuals who seek radical change. Hence, a crisis might be said to create some space for outsiders to join the political sphere and to use what Chernobrov (2018) calls threat narratives, often armed with blame-shifting, as it is made clear in the research by Yamey & Gonsalves (2020), Kreis (2017) and Busby, Gubler & Hawkins (2019).

Twitter is brought to the political sphere by Barack Obama (Anderson, 2017), named by Greengard (2009) as the 1st internet president. Sousa & Ivanova (2012) explain earlier the rhetorical space created in the Twitter by Obama. Anderson (2017) explains how this rhetoric space opened up a window for Trump's communicative strategies. As Twitter is unfiltered, it has allowed for the exploitation of emotion, which Weber (2013) believes to be rather noteworthy in politics. Ott (2017) explains the way Trump uses all of Twitters' defining features (*cf.* Chapter 3.2.3.). This research is followed by Ross & Caldwell (2020) and Ross & Rivers (2020), who extend the debate on the contrast between Trump's and Obama's distinctive

strategies. Blankenship (2020) explains the way Twitter helped Trump legitimize his political agenda, underpinned by the fact that, as contended by Enli (2017), Trump's image was formed by the popularity of his tweets and through the notion laid down by Rice-Oxley & Kalia (2018) that Twitter acts as a stage.

Third, the *Us-versus-Them* dichotomy is explored through the defining features of personal pronoun reference laid down by McCarthy & Carter (1994), Hogeweg & Hoop (2015) and Flores-Ferrán (2017). Moreover, Fairclough (2015) highlights the way politicians use shifts in personal pronoun reference and Glover (2000) related their use to topic of attitudinal direction. Proctor & I-Wen Su (2011) show how this can transmit nationalistic emotions. Fetzer & Bull (2008) focus on blame-shifting and responsibility, which is evidenced, in the work by MacWilliams (2016), to feature one of Trump's strategies (*cf.* Chapter 3.3.).

Fillmore (1997) introduces the idea that deixis relays identity, and Yuval-Davis (2010) considered this a possible issue to citizens' vindication of identity or exclusion. This conclusion is equally explored in Anderson's (2013) work on politics of immigration and Muller's (2018) research on the ethics of national identity. Lastly, Cikara, Bruneau and Saxe (2011) consider several issues related to identity in Trump's rhetoric.

Fourth, research on the cooperative principle may shed some light on the analysis of the corpus, following the fundamentals by Grice (1975), later explained by Chapman (2013) and expanded by Moeschler (2012), who studies both conventional and conversational implicature and by Karttunen (1975) and Horn (2012), who expand the theory of conversational implicature (*cf.* Chapter 3.4.)

3.1. Computer-Mediated Communication

The topic of Computer-Mediated Communication [CMC] has been, in the last decades, vastly researched, in an attempt to understand the way this medium can influence communication between people. Although most literature in the field terms it Computer-Mediated Communication (CMC), as is largely evidenced in the research by Walther (1992, 1994, 1996); Suchman (1985); Kiesler, Siegel and McGuire (1984); Baym (2015); Burgess and Baym (2020); Gershon (2017), among others. Davis and Brewer (1997) refer to electronic discourse instead, clarifying their sole focus on language, rather than on the medium. Focusing on language means they do research on the way the medium is used to achieve conversational goals; drawing a contrast between this specific medium and that of mainstream media (letters

or newspapers). According to Davis & Brewer (1997), this type of discourse is not a new structure of language but a new context⁴ where writing reads as speaking. This context differs from face-to-face (FtF) communication in terms of turn taking, mainly due to overlaps, interruptions and repetition (Davis & Brewer, 1997).

As stated by Walther (1992), this medium lacks in social context cues, “aspects of the physical environment and actor’s nonverbal behaviors” (Walther, 1992: 56), because there are no facial expressions, posture, dress or vocal cues (Walther, 1992). The lack of cues leads to self-absorption and flaming, and creates difficulties when someone is forced to converse in a situation they would rather not. This has led researchers to perceive CMC as an inherently impersonal medium (Walther, 1996), but functional and efficient at its core. According to Walther (1996), CMC appeared as a result of large computers being linked together for security and information redundancy reasons, where operators found they could also share short messages with each other. From there onwards they departed from the fact that CMC could also be a valuable tool for coordinating “emergency tasks among geographically dispersed individuals” (Walther, 1996:5). CMC could be also seen as a moderator (Walther, 1994), reducing emotional communication and increasing the focus of a work group (Walther, 1996). Being task-oriented, CMC solved the issues raised by earlier researchers, questioning if text would reduce coordination (Kiesler, Siegel & McGuire, 1984). Kiesler, Siegel & McGuire (1984) understood that CMC differed technically and culturally from traditional channels of communication, considering its speed and simultaneity even though culturally lacking in 1984. There was always expectation of immediacy, and some believed that CMC was too lean to be effective (Walther, 1996).

Researchers questioned the richness of media, which did not have generally rich nonverbal cues, but still formed communities and friendships (Walther, 1994). CMC was questioned in terms of insight and understanding of complex tasks (Walther, 1996), and was a medium for lean tasks, succinct messages and simple meanings (Walther, 1992). As Baym (2015) states, people react to new media in two ways: questioning the shallowness of communication and expecting opportunities for connecting with people. The potential of media seems to depend on their use, on the way utterances are coordinated or unfold in a logical way (Gershon, 2017). Gershon (2017) states that a medium’s novelty can be seen from the

⁴ In this piece of research, context can sometimes touch upon the meaning given by Catford (1965:31), namely: “'context of situation', i.e. those elements of the extratextual situation which are related to the text as being linguistically relevant: hence contextual”.

techniques for managing texts with context, still other approaches have been found, such as the ones for applying an ethnomethodological framework to synchronous interactions (Suchman, 1985) or those advocated by interactive media theorists, who are interested in the exchange of messages “vis-à-vis the medium” (Walther, 1994:473). Participants in diverse media will often rate it in terms of immediacy and self-expression (Gershon, 2017). However, according to Baym (2015), there are seven concepts to compare different media: interactivity, temporal structure, social cues, storage, replicability, reach and mobility.

Concerning interactivity there are three types involved: the social one (interaction between groups or individuals); the technical one (manipulation of the machine through the interface); and the textual one (interpretative interaction between users as produced by Baym, 2015). In terms of temporal structure, this can be synchronous, as in face-to-face or instant messaging or asynchronous, as in email or voice mail.

Synchronicity in media reassures proximity among people, encouraging playfulness (Baym, 2015), even though it requires participants to schedule engagements and, if several people are involved, it becomes harder to answer several messages of diverse kind. According to Baym (2015), asynchronous communication allows for people to manage face, having enough time to strategize a response. Thus, CMC has evolved from an automatic cold and unsociable medium (Walther, 1992) to a medium in which people find new ways to reflect towards their identities (Gershon, 2017). Gershon (2017) puts forth that “media do not always precede media beliefs”, so issues may occur when utterances travel through different media.

Since online media is ever evolving, it is noteworthy to focus both on its possibilities of application and consequences, rather than solely on the technical features of specific media. Baym rightly added back in 2015, “within four years, three-quarters of online traffic was email” (Baym, 2015:13). What the author calls “the textual internet” consisted of: talk, IRC (Internet Relay Chat), IM (Instant Messaging), Mailing lists and MUDs (Multi-user Dungeons). With the expansion of media into the world wide web, new forms emerged: “web boards, blogs, wikis, social network sites, video and photo sharing sites, and graphically intensive virtual worlds” (Baym, 2015: 16). In blogs, for example, one could find communities being created among shared topics of interest. Social network sites [SNS] are places in which individuals can share messages (by uploading them) diverse media “(photos, videos, music, links, and more)” and can create a connection through friending or following. Facebook, Twitter and Instagram are general examples of SNS. Spotify and YouTube can be seen as specific types of SNS (music

sharing and video sharing respectively). Baym (2015) asserted that, “we live in a ‘polymedia’ environment”, meaning that one’s lives are intertwined with media, which itself can be embedded in other media. To both digital media and its predecessors, individuals have raised questions with regards to authenticity and well-being, considering its push for continuous interaction (Baym, 2015). Scholars have also questioned the possible harmfulness of stored information and the issue of online deception (Baym, 2015), a topic which is not explored in this piece of research. When identities are created online, these become fragile when spanning from one context to another one, because users are given the arbitrary power to assume the way communication is supposed to take place (Gershon, 2017).

3.1.1. Twitter

Twitter is an SNS launched in March 2006. It allows users to “maintain a public web-based asynchronous ‘conversation’” (Murthy, 2013:1,2) through messages of 280 characters (Anderson, 2017), restrictions through which users communicate (Mancera & Pano, 2013). Tweets (messages created through/in Twitter) are public and accessible on the user’s profile. According to Murthy (2013), in 2013, 40 world leaders had verified accounts (verified accounts are given to celebrities or individuals of public interest, distinguishing real accounts from fake ones) and 200 million tweets were sent every day. In 2017, 300 million monthly users were recorded (Anderson, 2017). Tweets can be sent from both phones and computers, as well as websites, other than Twitter, if these have embedded software.

The dialogue in Twitter occurs through the at-sign @ (Murthy, 2013) similarly to other social networks. Group discussions seem to be created through the use of hashtags # (Murthy, 2013), which categorizes the topic and organizes it next to other tweets with the same hashtag. Tweets can also be directed at specific individuals and one can address any other one on Twitter (Murthy, 2013). A user’s profile stores all his/her tweets, which are shown in reverse chronological order, from the newest to the oldest. Because of this feature Twitter is reminiscent of blogs but, as messages are much shorter, it is often termed as a microblog. Engagement is a feature that is sought after in Twitter; it can be measured through likes, retweets and replies (Anderson, 2017). According to Anderson (2017), engagement is an important tool for politicians, who loop tweets which have higher engagement, measured by the following features: self-preservation, action and participation, uses and gratifications, positive experiences, use and activity counts along with social context.

Anderson (2017) advanced that, in 2016, Trump tweeted on average 7.5 times a day; in 2020 he tweeted, on average, 50 times a day up to a record of 200 times a day. His first tweet was in May 2009 and his last one in January 2021. On the whole, the former United States president tweeted 56 572 times, including retweets. At the beginning of 2021, Donald Trump was banned from Twitter after having violated Twitter's terms of service; therefore, he is no longer registered there.

Several researchers focused their attention on the 2016 elections, particularly by connecting the issue of fake news with the fast dissemination of information in social media. In Twitter, fake news spread faster than factual news because these are more attractive to the public (Bovet & Makse, 2019) and because of the tweets sent by influencers or alpha users who have many followers worldwide (Anger & Kittl, 2011). This results in the creation of communities with shared beliefs, echo chambers (Bovet & Makse, 2019) in which news, both factual and unsubstantiated, spread faster and, in some instances, virally. Grinberg et al. (2019) identify fake news outlets as those which seem legitimate but lack the norms of an editorial to be credible. They further state that fake news spreading fast in social media may create a problem for democracy, thereby requiring citizens to be factually informed.

Powerful influencers, as it is the case of political figures, can change citizens' lives and jeopardize their position by disseminating fake information. So is the case in which Trump recommended injecting disinfectants (Cuello-Garcia, Pérez-Gaxiola & Amelsvoort, 2020). In these instances, politicians are called to weaponize social media and must therefore be held accountable (Cuello-Garcia, Pérez-Gaxiola & Amelsvoort, 2020), since it has become ever more customary for the political elite to promote actively fake news (van der Linden, Roozenbeek & Compton, 2020). Due to the spread of fake news in social media by well-known public figures, much disbelief is created around the true recommendations of medical experts, and people start to envisage the virus as a weapon, created in a lab for the purpose of triggering a world war. These people may then go further and even refuse to follow health guidelines and refuse vaccination (van der Linden, Roozenbeek & Compton, 2020), as reported in the media on several occasions ever since 2020.

Due to the stated above, social media play an important role in crisis management, i.e., “a process consisting of activities of evaluation of crisis signs, taking and applying necessary precautions in order to recover from the crisis with minimum loss” (Civelek, Çemberci & Eralp, 2016: 113). This is pertinent because the spreading of fake information can diminish the

effectiveness of the countermeasures against the virus (Cinelli et al., 2020). Cinelli et al. (2020) posit that Twitter helps amplify rumours; besides abandoning traditional news influences social perception and manipulates narratives. They further state that by looking for information online, social media users gather information which adheres to their own view of the world, ignoring any further piece of information that goes against their beliefs, thereby forming groups with shared narratives. This is what Naeem and Bhatti (2020) call an infodemic, i.e., an excess of information around a topic, which makes the issue of the topic harder to solve.

3.2. Political Rhetoric – From its Defining Features to the Twitter Age

People look up to their leaders for leadership (Wood, Owens and Durham, 2005) and their rhetoric defines the political reality (Zarefsky, 2004) through a ritual marked by language choice (Goffman, 1983). Murphy (2009) advocated that expertise is a sought-after value in 21st century politics and Zarefsky (2004) observed that, by commenting on reality, a president may alter the way events are understood by audiences; he can highlight or hide elements of a topic; influence them and focus on their attention on the way they handle information, identify causes and propose remedies along with inviting judgment on individuals or policies at large. Thus, this section discusses political rhetoric, the rhetoric of crisis and how political rhetoric occurs through social networks, particularly Twitter.

3.2.1. Political Rhetoric

Windt (1986) states that the president has three powers: constitutional and statutory, political power and public opinion. When it comes to political rhetoric, its discipline focuses on the study of persuasion by presidents, namely the way a president may obtain, maintain and lose the rapport with his/her followers. Its material consists of any communication by the president (Windt, 1986). The presidential rhetoric, when perceived from the theoretical view of humanities, deals with unique cases and repeating patterns, and seeks a richer understanding on the subject matter (Zarefsky, 2004) at hand. Zarefsky (2004) stated that the presidential rhetoric reflects a presidents' view of the world around him. That is often seen as an art, with many layers, requiring its interpretation. The rhetor, the president, makes choices in order to persuade a specific public, enabling him/her to achieve the goals he/she has in mind. Through their linguistic choices, presidents can create associations, by expanding the existing terms and disassociation, by breaking terms into parts and favouring one part over the other. They can also identify and define situations, condense different meanings into one and shift frames of

reference. In short, they are intended to perceive something through a different lens (*ibidem*, 2004).

Apart from the features listed so far in the realm of communicative strategies, it is worth mentioning the frame shifting allows for the creation of conceptual metaphors, like the WAR metaphor (Lakoff, 1993; Koller, 2011; Lakoff & Johnson, 2003). The WAR metaphor is common in business discourse, yet various researchers identify conceptual metaphors in populist rhetoric, where they are used as a strategy to polarize audiences (Demata, 2017). Chilton (2017) further states that “the people” is a conceptual metaphor focused on accumulating hate speech and prejudice on “the other” (Hartmann-Mahmud, 2002).

Populist rhetoric associated with Trump’s communicative strategies (Hidalgo-Tenorio & Benítez-Castro, 2021) is, according to Lacatus (2019), a type of rhetoric aimed at vilifying the elite (a threat to positive face, as discussed by Brown & Levinson, 1987) which are said to be causing a crisis that only the collective voice of citizens can solve. Populism comes with promises for the betterment of political order (Lacatus, 2019) and can be evidenced in two ways: through left-wing populism and right-wing populism, corroborating Hidalgo-Tenorio & Benítez-Castro (2021). Although left-wing populism is focused on anti-capitalist opposition to elites (banks, government, etc.); right-wing populism revolves around “antagonism towards hybrid societies, leading to fear of losing social status and a growing hostility towards minorities” (*ibidem*: 2). Accordingly, on the right side of populism, there is a contrast between the vilification of the OTHER (outgroup relations) and the celebration of presidential achievements (ingroup relations), pulling on the glories of the past (pathos), to a golden age (Lacatus, 2019). Lacatus (2019) advanced that, according to right-wing populists, the people are pure, while minorities and immigrants are often represented as problematic (threat to the positive face of interlocutors). The rhetoric of populism associated with Donald Trump is known as emotional, direct, uncivil and simple, as largely researched by Lacatus (2019), Appel (2018), Oliver & Rahn (2016), Hidalgo-Tenorio & Benítez Castro (2021) and Savoy (2017), among others.

Trump’s presidency shifted the norms of foreign policy (Lacatus & Meibauer, 2020), by exploiting his own narrative and emotional lines to close the gap between language and action without actual changes to the real world (Appel, 2018). His rhetoric is categorized as simple, anti-elite and with the use of collective language (Oliver and Rahn, 2016), particularly the personal pronoun “we” (supposedly inclusive and marking ingroup relations) and the

metaphor “the people” as contrast (outgroup relations). His supporters are observed to have “high levels of conspirational thinking, nativism and economic insecurity” (Oliver and Rahn, 2016: 190). The core of ‘Trump-speak’, as Homolar and Scholz (2019) call it, is a three-fold rhetorical strategy. First, he states what is wrong with the world, then he identifies who is responsible for the crisis and, finally, he gives an abstract solution to the problems by promising to restore the “great past”, to make America great again (a frequent collocation and phrase in his campaign and speeches) (Homolar & Scholz, 2019). Trump’s presence in the White House was reported to create incoherent policy processes, to bring up infighting and to create conflict between him and the staff (Lockhart, 2018). Trump’s rhetoric is explicitly emotional and implicitly opinionated, making up to his persona as a saviour of the United States (Hidalgo-Tenorio & Benítez-Castro, 2021), in a climate that is more emotional than logical (Sanchez, 2018): pathos over ethos and logos.

According to Hidalgo-Tenorio and Benítez-Castro (2021), for Trump, truth does not matter and supporters are drawn to what situations feel like, instead of what they actually are. They end up defending everything he says or does (Sanchez, 2018). Through repetition, Trump inculcates points of view, even lies, to persuade citizens (Savoy, 2017). Savoy (2017) considers that his spoken style is direct and aims at action, repeating short sentences and expressions. These make him seem like an energetic and masculine figure who can actually save the United States. Researchers see Trump’s rhetoric as a language learned from his time as a reality TV star (Hidalgo-Tenorio & Benítez-Castro, 2021); some even draw a line between his language and supremacist groups (Sanchez, 2018), while others consider his language one of vulnerability (Kelly, 2019). Sanchez (2018) states that Trump’s language choice has similarities with the one of supremacist groups, although hidden in subtext through textual winks and concepts, such as honour and patriotism. The author advocated that textual winks allow Trump to use language that connects him to an outside group, white supremacists, while keeping rapport with his party members and audiences. On the same spectrum, Kelly (2019) observed that Trump’s choice of language and topics allowed for the transformation of victimization into virtue. His emotional outburst also disclaimed followers of all legal responsibilities (*ibidem*).

3.2.2. The Rhetoric of Crisis

Wodak (2021) suggested that the term crisis is always understood negatively and that this negativity is further inflated by commentaries in news media and by politicians. The author

claims that the spread of information about a crisis in media ignites fear and powerlessness, leading citizens to expect leaders to instruct them to survive. Furthermore, Wodak (2021) states that there is a “dread of death” in the afore said media, because of the repeating images of sick citizens in hospital beds, as well as images of cemeteries and/or crematoriums. Much in the same wavelength of populist politicians, any failure is instantly transformed into credit, meaning that politicians claim to be saviours of the nation (*ibidem*). This is what Wodak (2021) calls a rescue narrative, in that by blame-shifting, politicians overcome any problems and simultaneously manipulate the citizens’ perception. Governments have different strategies to deal with a crisis and some even instrumentalize the pandemic, seen as an opportunity, for their own authoritarian claims (*ibidem*). The threat to the economy and politics establishes an opportunity for patriotism and nationalism, and in some ways lays the grounds for an *Us-versus-Them* narrative (*ibidem*).

During a crisis, such as a pandemic, the government must employ strategies that allow them to convince citizens into following the rules, that is, one that evokes emotions through fallacies, particularly fear, which forces citizens to act accordingly (Wodak, 2021). Citizens are forced to comply with governmental decisions to protect their lives, by means of what is called liquid fear (*ibidem*). It results from a view of the world as insecure and vulnerable. In these instances, politicians are granted all power and may even punish journalists when they believe their information to be “fake news” (*ibidem*). This is much common with right-wing populists, who attack “mainstream media actors and outlets which try to find out more on the subject, to verify and question official statements, to change the framing of the pandemic by the government and so on. “(Attila, 2020:1).

Trump’s success happened thanks to an anti-establishment crisis narrative, which divided the domestic and international contexts into *Us-versus-Them* (Homolar & Scholz, 2019). He spread the idea that the country was at risk and that citizens’ welfare was sold and destroyed on a regular basis (Hidalgo-Tenorio & Benítez-Castro, 2021). Particularly during the COVID-19 pandemic, the US have been more polarised than ever before and this division has become the new normal cline (Hidalgo-Tenorio & Benítez-Castro, 2021). According to Hart and Tindall (2009), the use of labels such as “crisis” or “scandal” is perceived as a political weapon, which can mobilize media, challenge the government and force the creation of a narrative to explain the state of affairs. Crisis narratives push for radical changes and benefit individuals who want to change the status quo, like outsiders of the political sphere (Lacatus,

2019). Following the research by Hart and Tindall (2009), one can understand that crises are understood inside framing contests. This means that there is a discussion between actors who want to exploit the opportunities presented by the crisis. There are four types of framing contests: the nature and severity of a crisis, its causes, the responsibility for its occurrence or escalation and its policy implication, and actors exploit these to fortify their authority, draw or not draw, the public attention, and give rise to new policies (Hart & Tindall, 2009).

The aforementioned framing contests serve as a context for political debate, in which politicians can assume one of three types. Hart and Tindall (2009) state that type 1 includes business-as-usual politicians, who minimize occurrences; type 2 covers crisis as threat politicians, who defend the status quo and its agents; type 3 concerns crisis as opportunity politicians, who expose weaknesses in the government and use blame to create change. When it comes to the severity of the crisis (Hart & Tindall, 2009), Donald Trump seems to address several types through different contexts. At the beginning of the COVID-19 crisis, he can be seen to stand for a type 1 position, minimizing the significance of the event and its effects upon the US, but also taking a type 3 position by maximizing the threat when it comes to the foreigner, the OTHER (Chernobrov, 2018). In terms of causality (Hart & Tindall, 2009), Trump embodies a mix between type 1 and type 3, not being accountable for his mistakes, but shifting blame to specific individuals or organizations (Yamey & Gonsalves, 2020; Kreis 2017; Busby, Gubler & Hawkins, 2019). In the context of the political game (Hart & Tindall, 2009), Trump tries to blame past office holders (Yamey & Gonsalves, 2020), hoping to damage their reputations and, in terms of the policy game (Hart & Tindall, 2009), he creates opportunities for reform and change.

During Trump's presidency, attacks on media were very frequent, and his dislike of media made him create the Fake News Awards (Attila, 2020). Attila (2020) advocates that the use of Twitter is a strategic ploy by the White House, which limits the possibility of the administration being questioned on their decisions. The author further advanced that this enabled Trump to downplay the pandemic by creating his own picture of what is true or false. Furthermore, for Trump, asking questions during one of his conferences was considered immoral (*ibidem*).

3.2.3. Political Rhetoric in the Twitter Age

When running for elections, politicians are claimed to use any possible advantage (Greengard, 2009); in recent times, the internet or social media in particular, has become one

powerful tool for politicians to vindicate their beliefs among audiences. Many researchers have looked into Obama's team use of technology⁵, thanks to Obama bringing Twitter to "the forefront of American politics" (Anderson, 2017:36), creating a space for the comments of politicians and political discussion. Knowing how important emotions are in politics (Weber, 2013), Twitter allows for networking and raising enthusiasm (Anderson, 2017). By using this new media, politicians can bypass both the congress (Greengard, 2009) and the press (Anderson, 2017), neglecting more traditional forms to disseminate information and addressing followers directly. Traditional media are no longer the only means for politicians to express their rhetorical moves (Sousa & Ivanova, 2012). This freedom has allowed citizens to make themselves heard (Greengard, 2009), giving the chance for political discussions to happen (Anderson, 2017).

Anderson (2017) asserted, "What Trump lacked in policy, he gained in authenticity with the voters" (p. 37). This was made possible by means of what Ott (2017) has identified as Twitter's defining features: simplicity, impulsivity and incivility. Trump's use of Twitter is scriptless (Lockhart, 2018) and impulsive, full of virulent critiques (Lacatus, 2019), insults, in a language that is called dark and violent (Ott, 2017). His use of Twitter is unprofessional (Ross & Rivers, 2020; Ross & Caldwell, 2020), unlike Obama, whose media team authored all tweets (Ross & Caldwell, 2020), Trump's language was rated at 3rd or 4th grade reading levels⁶, making it approachable to any audience (Ott, 2017). Trump did not sound like the usual politicians (Ross and Rivers, 2020), but was presented as an outsider (Homolar and Scholz, 2019). Trump benefitted from Twitter's affordances, by using its restrictions (Mancera & Pano, 2013) to communicate his political agenda (Blankenship, 2020) together with a strategy of legitimization of personal beliefs and values while delegitimizing those by his opponents, often through nicknaming (Ross & Rivers, 2020). It is common practice in Twitter that users share messages with a high level of engagement with their audiences (Anderson, 2017). Trump particularly used Twitter to influence beliefs and ensue retweets, spreading his messages widely. It is argued that retweeting does not always have a reason other than imitating others who are also sharing messages (Anderson, 2017). According to Enli (2017:37) "his image as a candidate was largely formed by his widely circulated tweets, which were often quoted and debated in the mainstream media." which was a result of messages that were seen as polarizing (Kreis, 2017) and constantly delegitimizing the press (Anderson, 2017). Anderson (2017)

⁵ Often focused on single speeches or in specific domains (Sousa & Ivanova, 2012)

⁶ When run through the Flesch-Kincaid grade-level test (Ott, 2017)

claimed that tweets criticizing the media (Atilla, 2020) had the widest engagement by audiences. Trump retweeted favourable news outlets while ignoring others by calling them “fake news”. Negativity is a tool used by Trump, in terms of pointing out others’ weaknesses, and Twitter has helped both to amplify and simplify this approach, making Trump’s negativity more frequent and addressing a wider range of targets (Ross & Caldwell, 2020). Even if what is tweeted is exactly what he presumably thinks (Ross and Rivers, 2020), Trump’s use of Twitter can be understood as a strategy to legitimize his populist agenda (Blankenship, 2020), since he needed a crowd (Rice-Oxley & Kalia, 2018) to push “his various spectacles (e.g., entertainment, business, and presidency) supported by the notion of “winners” and “losers” (Blankenship, 2020: 1), which Twitter provided.

3.3. *Us-Versus-Them* Rhetoric: Indexical Expressions and Identity Issues

Personal pronouns are the linguistic elements which are often connected to the speaker/addresser and to the hearer/addressee (Hogeweg & Hoop, 2015). Hogeweg and Hoop (2015) observed that the interpretation of pronouns is pragmatic in nature: first person pronouns may not comprise the speaker/addresser and second person pronouns may not refer to the hearer/addressee. Interpretations of a second person pronoun can be considered deictic (Hogeweg & Hoop, 2015) and deixis itself attracts the attention of researchers of political rhetoric (Sousa & Ivanova, 2012). Deixis is related to the orientation of a speaker and listener/hearer concerning person, time and space (McCarthy & Carter, 1994). Political research on deixis focuses mainly on first-person plural deictic pronouns (Sousa & Ivanova, 2012), which mark dissimilar groups through inclusion and exclusion. In personal subject pronouns there is a contrast between proximal and distal reference, through indexical expressions (Flores-Ferrán, 2017). In political discourse, politicians can show how they position themselves through the shifts in indexical expressions (Fairclough, 2015). Through the use of the first-person pronoun reference in the plural, i.e., we, speakers may be hoping to index themselves in different groups, depending on the context of communication (Flores-Ferrán, 2017). According to Glover (2000), this shift can give a clue into a speaker’s, Trump’s, attitudinal orientation, aiming at, perhaps, evoking nationalistic emotions (Proctor & I-Wen Su, 2011) or raising solidarity (Flores-Ferrán, 2017). Fetzer and Bull (2008) advance that personal pronouns can help politicians distance themselves from responsibility, thereby pronoun shifts can help to minimize roles, criticism and unfavourable commentary on their part. In his research, Flores-Ferrán (2017) found that Trump’s manipulation was at stake when

he shifted from distal to proximal expressions. These shifts both occurred when he self-promoted or advocated his own decision-making.

Trump's use of *Us-versus-Them* rhetoric allowed him to pull on voters and win the 2016 election (MacWilliams, 2016), and personal deixis can be seen to relay interlocutors' identity (Fillmore, 1997). Thus, this dichotomy of *Us-versus-Them* can be seen as a question of identity (Yuval-Davis, 2010). MacWilliams (2016) explains that this strategy, as employed by Trump, works either by manipulating voters through increased real and imagined threats or by showing that the OTHER⁷ holds different values, that Trump recognizes as a threat to the nation. This is a strategy of isolationism, through a calling to get the country back and making it "great again", which can be far superior than the "other" (Görlach, 2018). Trump's rhetoric creates an identity issue and fosters the labelling of the "failed citizen"; which is the individual seen as incapable of living with the same values as the nation (Anderson, 2013). This individual is seen as a threat to local communities, becoming a target of the rhetoric on the OTHER. Identity politics create categories of belonging, including accepting a leader as the representative of the collective identity⁸ (Yuval-Davis, 2010). Identities themselves are seen by Yuval-Davis (2010) as narratives, which are "stories that people tell themselves and other about who they are, and who they are not, as well as who and how they would like to/should be" (Yuval-Davis, 2010: 266). In politics, the identity is national and can be seen in two ways. According to Muller (2008), one view considered all people living within the nation's borders part of the nation, without divisions by race, ethnicity or religion while the other view, ethnonationalism, only includes people with shared common language, faith and ethnic ancestry. This second view is common in the U.S. history, where only specific groups of people were reported to have been considered part of the nation drawing on the notions of extended family and blood ties; often originating from English-speaking countries; being white or protestant; arriving from northern Europe (Muller, 2008). This gap created between *Us* and *Them* is frequent in conflict and at war (Yuval-Davis, 2010). By means of a forced belief of an embracing first person pronoun reference in the plural (Muller, 2008), the OTHER is believed to be demonized (Yuval-Davis, 2010). This creates clashes in empathy (Cikara, Bruneau, Saxe, 2011). According to Cikara, Bruneau and Saxe (2011), gaps in empathy lead to indifference towards the suffering of the other and create spaces where further harm is aggravated.

⁷ The "other" is, according to the literature review, any figure considered by the leader as a threat to the nation and its values.

⁸ Collective Identities give order and meaning to a nation (Yuval-Davis, 2010).

3.4. Conversational Maxims and Flouting

In his work, Grice (1975) states a general difference between what a speaker says and what he implicates. The topic of implicature has been of interest by several researchers (Karttunen, 1975; Moeschler, 2012; Horn, 2012; Chapman, 2013; Goodman & Stuhlmüller, 2013), some of which borrowing from the work by Grice, some adding to it and others extending the principles to a new context of analysis.

Grice (1975) states that the word SAY is the closest to the conventional meaning of an utterance, but what is said “must be understood in terms of what philosophers define as ‘meaning’” (Moeschler, 2012:409). What is said may be the conclusion of a “linguistic computation” (*ibidem*), which suggests a truth value proposition. The author further stated that Grice’s impression of what is said could not have been just a linguistic notion but a “full proposition with a truth value” (Moeschler, 2012). Grice’s aim was not to find just what a speaker means by the words he/she uses but to look into the literal meaning of words (Chapman, 2013). In a sense Grice’s work was not just descriptive but of expository kind. Grice (1975) familiarised the term implicature as a way to explore speaker meaning beyond the literal meaning (Chapman, 2013). Implicature was illustrated with the bank example where a speaker (A) asks a hearer (B) how a third party (C) is doing in his new job. B replies “quite well, he likes his colleagues, and he hasn’t been to prison yet” (Grice, 1975:43), in that B may be implying some meaning through his words. As Grice (1975) advances, C might be prone to stealing from the bank or perhaps hating his colleagues. In this example Grice (1975:43) uses the words “implied, suggested and meant” to explore the meaning conveyed (Moeschler, 2012). The answer to this dilemma may be in the context shared between speaker and hearer; it would not require further questioning (Grice, 1995) because there is a sense of common ground created via a set of propositions that participants may take for granted (Karttunen, 1975).

Grice (1975) proposed the cooperative principle [CP] which states “Make your conversational contribution such as is required, at the stage at which it occurs, by the accepted purpose or direction of talk exchange” (Grice, 1975:45). This principle is supported by nine maxims of conversation, “grouped in four Kantian categories” (Moeschler, 2012) – Quantity, Quality, Relation and Manner. The maxims, as explained by Grice (1975) are the following: the maxim of quantity presupposes one makes one’s contribution as informative as it is required (for the current purposes of the exchange) and that one does not make one’s contribution more informative than it is required. The maxim of quality falls a supermaxim – try to make your

contribution one that is true – requiring one not to say what one believes to be false and that one does not say what one lacks adequate evidence to say. The maxim of relation simply states that one must be relevant. The maxim of manner pursues a supermaxim, i.e., be perspicuous, in that it presupposes one must avoid obscurity of expression and ambiguity; one must be brief (avoiding unnecessary prolixity) and orderly. Grice does admit the existence of other maxims (e.g., aesthetic, social, moral) which can also create implicatures.

In his work, Grice (1975) explains the maxims making use of metaphors. For instance, it is stated on the maxim of quantity that a fitting amount of information is to be present in conversation (Chapman, 2013). This is explained by B assisting A to repair a car; when A asks for four screws, B is expected to give four and not two or six. The maxim of quality is illustrated by a situation in which the hearer expects the speakers to be honest; if A asks for sugar while making a cake, he does not want to be offered salt. The maxim of relation may be followed when the hearer expects appropriateness in the conversational exchange, while mixing the cake, A does not want to be handed a book or a piece of cloth. The maxim of manner follows the expectation that contributions are clear and reasonable; this category does not consider the information provided but with the form it takes (Chapman, 2013).

The maxims are used to describe what happens when interactional expectations are not satisfied (Chapman, 2013). A maxim may not be fulfilled in various ways, a speaker may violate a maxim, misleading the interlocutor, he/she may opt out from both the maxims and the cooperative principle while not cooperating due to unwillingness or inability, for instance by saying “my lips are sealed” (Grice, 1975:49). A speaker may face a clash by fulfilling one maxim and violating another one, as Grice exemplifies, a speaker may be unable to fulfil the maxim of quantity (of being informative) without violating a maxim of quality (to have evidence to what is said). Finally, a speaker may flout a maxim, this means, to deliberately fail to fulfil it. On the assumption that a speaker is not opting out or unable to fulfil a maxim he/she must be creating a conversational implicature through the exploitation of the maxims (Grice, 1975). A hearer cannot dismiss what the speaker says as uncooperative as there is some certainty about the current talk exchange and clear expectations of cooperation; therefore, interlocutors have to try to interpret what is meant by what is said (Chapman, 2013). Chapman (2013) adds that both parties, speaker and hearer, understand that there is some hidden meaning being encoded, so there is an effort to understand what is implied.

The flouting of maxims occurs in a myriad of situations, Grice explains it in his work, *Logic and Conversation*. The first maxim of Quantity may be flouted when less information is given than what is required even though the speaker could be more informative if he/she wanted. As Grice (1975) puts it, A is writing to recommend a student for a job, but on the letter, he/she does not specify any of his relevant qualities, writing only that he attended courses. Since this speaker cannot be opting out, since the desire to be uncooperative would mean simply not writing a letter and he/she cannot claim ignorance since it was about his/her student, the hearer/addresser of the letter can only assume that the speaker is implicating something – that the student is not good for that position. Another way to flout this maxim is by the use of tautologies, comments that are not informative, like “War is war” (Grice, 1975). The second maxim of Quantity can be flouted when a speaker, for example, overexplains or over justifies what could have been a straightforward answer. This creates doubt about the piece of information provided, and it becomes debateable if the speaker utters something truly (Grice, 1975). The first maxim under Quality can be flouted in several ways. Firstly, through the use of irony, a speaker says something that he/she does not believe implying that he/she wants to get some other meaning across, often the opposite. Secondly, through metaphors which are categorically false since they attribute to a target the qualities of something different. Thirdly, through the use of meiosis, “Of a man known to have broken up all the furniture, one says He was a little intoxicated” (Grice, 1975:53); and lastly through the use of hyperboles like “Every nice girl loves a sailor” (Grice, 1975:53). The second maxim of quality can be flouted when in a “suitable context, or with a suitable gesture or tone of voice” (Grice, 1975:53) something is said without any evidence to support it. According to Grice (1975), the maxim of relation is flouted when, for example, social gaffes are committed, i.e., when a speaker says something rude in a group and another member of the same group replies with something unrelated, showing that the previous comment should be ignored.

There are several ways to flout the maxim of Manner, in particular the supermaxim “be perspicuous”: through ambiguity, because it is a choice and it can be interpreted in several ways with one interpretation being less apparent than the other; also through obscurity, when two interlocutors want to exclude a third party that might be listening, they might speak in code, making it impossible to interpret by anyone else but themselves; finally the speaker may fail to be brief or succinct, perhaps through a comic undertone in an utterance, following the example set down by Grice, on a singing performance, the singer might not quite catch the

notes of the song and as such instead of commenting “She sang song x”, a commentator might say “she made noises which resembled x”, implicating that she sang badly.

In computer-mediated communication the confidence of an interlocutor enables him to flout maxims more frequently and as such try to imply meaning in more creative ways than ever before (Barbulet, 2013). Barbulet (2013) identified the use of maxims in British newspaper blogs while other authors like Afaldi and Kurniasih (2019) focused on Instagram comments. Particularly focused on Twitter, Carr (2017) created a technique to identify the conversational maxims in tweets. For the author, the maxim of quantity was found when a tweet contributed sufficiently to a topic and provided original information, while at the same time flouting the maxim when it presented more than one subject or did not add anything new to the discussion. Carr (2017) further identified that the maxim of quality was highly relevant during the 2016 elections (in the United States) because the candidates were distrusted by the general public, as such to follow the maxim, tweets need to be truthful and provide evidence of the said truth. Concerning the maxim of relevance, the author states that it is flouted when a tweet is irrelevant (Carr, 2017). Lastly, concerning the maxim of manner, the author explains that a tweet must simply be well organized, concise and intelligible, and that can fail when tweets are context specific (*ibidem*).

3.4.1. Conversational Implicature

According to Grice there are conventional implicatures and conversational implicatures, in this piece of research the focus is on the latter. Conventional implicatures are determined from the meaning of words and some of these words are known for creating an implicature (Chapman, 2013). Conventional implicatures imply a link between two utterances. This link does not change the truthfulness of the utterance (Moeschler, 2012). According to Horn (2012), some researchers do not accept the existence of conventional implicatures. Some argue so following the relevance theory and it is stated that this categorization creates a problem with understanding what is said and what is meant. Karrttunen (1975) states that conventional implicatures do not stem from the conversational maxims but from a conventional meaning found in words. The *implicatum* can be detached from what an utterer/speaker says and it is possible to find other ways to transmit the same meaning (Karrttunen, 1975). There is a need for a common ground to be established among interlocutors, and that both parties organize their dialogue in a way that their conventional *implicata* make sense (Karrttunen, 1975).

On the other side of the spectrum there is conversational implicature, as Grice (1975:49) puts it “A man who, by (in, when) saying (or making as if to say) that p has implicated that q, may be said to have conversationally implicated that q”. This is only true if he/she is observing the maxims and the cooperative principle, if he is aware that q is needed to make his/her meaning come across and if he/she realizes that the hearer can grasp the supposition made (Grice, 1975). Some instances of conversational implicature are straightforward, presupposing that the speaker can be observing the maxims, but less relevant for analysis. More fruitful examples are those in which a speaker is not particularly following the maxim (Chapman, 2013). These implicatures often arise from the flouting of a maxim but are different from contextual implication, because these entail the relation “between a speaker (not a sentence) and a proposition” (Horn, 2012). When this happens, and knowing that a speaker is not willing to deceive the interlocutors, a hearer may be unwilling to accept what he/she hears as uncooperative. The level of cooperation makes the hearer want to find a hidden meaning and there is a process of interpretation of what is said (Chapman, 2013).

Conversational implicatures must be able to be worked out, while implicatures that are intuitively understood are conventional. According to Grice (1975), to work out the presence of a conversational implicature, the hearer should check the relevant data: he/she must know the conventional meaning of the words used, he/she must know of the Cooperative Principle and the Maxims, he/she must understand the context of the utterance and know the context of the conversational exchange. An implicature is not conveyed through what is said, “but only by the saying of what is said, or by ‘putting it that way’” (Grice, 1975:58). All conversational implicatures are cancellable⁹, either by what is said next or by the context (Chapman, 2013). Chapman (2013) states that changing the words in the utterance does not change what the speaker implicates, he understands that conversational implicatures are expected since they result from a calculation, where a hearer infers through the conventional meaning and the maxims.

3.4.1.1. Generalized conversational Implicature

Generalized conversational implicature [GC] is the approach that is the closest to the form of words used. These implicatures occur by default if there is no context to prevent them (Chapman, 2013). Grice did not focus his attention on this type of implicature. The author left

⁹ An implicature can cease to exist if a speaker states that he has opted out (does not want to be cooperative) or if one can understand from the context that the speaker does not wish to be cooperative (Grice, 1989)

some examples of generalized conversational implicatures in action through the indefinite article “a”. For instances when it is stated that “X went into a house”, a hearer might understand that the house does not belong to X. Likewise when the statement is: “I have been sitting in a car all morning”, the interpretation is left open and it is not clear whether the car belongs to the speaker identified by the first-person pronoun reference or not. Lastly when he/she utters “I broke a finger yesterday”, one might assume that the speaker is implying that he broke someone’s finger and not his own (Grice, 1975).

According to Grice (1975), there are three forms of the expression “an X”, (i) “just any X”, (ii) “an X remotely related to someone in the context” and (iii) “an X closely related to someone in context” (Chapman, 2013:165). Another example of this type of implicature in action can be found in “My wife is in Oxford or in London” (Horn, 2012:60). The speaker does not know in which of both locations (*ibidem*). The nondetachability behind these implicatures is carried by a “familiar, nonspecial locution” (Grice, 1975:58). Moeschler (2012) calls these implicatures as “scalar implicatures”, borrowing his approach from Horn’s (2012) research.

Moeschler (2012) states that the first researcher who focused on the general and systematic behaviour associated with language choice was Gazdar (1979). The latter aimed to understand the complex pragmatic and semantic relationship between quantifiers like “some”, which are known to create ambiguity in meaning and may be seen to implicate not all. According to Moeschler (2012), Horn analysed this generalization further in the theory of quantitative scale. Horn (1972) realized that there were no negative features, yet there were positive universals and positive particulars as well as negative universals. Some positive particulars are weak and generate scalar implicatures – “or” denies “all” and “some” negates “all”. As Horn (1972) further puts it, what is implicated in “some are” and in “some are not” is the same communicatively speaking; “some are and some are not”. A speaker saying “or” meaning “all” might be incurring in a lexical error, or he/she might be a follower of Grice and know that he cannot say “all” because that it is false (Moeschler, 2012). As such, “or” is the most fitting for the second maxim of quality and triggers a scalar implicature. According to Moeschler (2012), Horn’s theory of quantitative scale accounts for the triggering of scalar implicatures, particularly “the asymmetry between semantic entailments and scalar implicatures” (Moeschler, 2012). This explains why lexical items are not always ambiguous since their meaning potential is constrained by the principles of pragmatics. Horn (2012) states that scalar implicatures depend on what is not said, but could have been, as explained by the

author: a speaker saying some implicates not all and while a stronger proposition could have been used, the speaker might not have done so for reasons of brevity, relevance or politeness.

4. Methods, Methodologies and Procedures

4.1.Data Collection

The corpus (Sinclair, 2004) for this study comprises tweets collected in two periods, starting from a pivotal point – when COVID-19 was first mentioned by president Trump in Twitter. Corpora collection was made feasible by means of an online compiler tool (<https://www.thetrumparchive.com/>), which contains no copyright and allows filtering by date. This research study collected all tweets posted by Trump within a 10-month period, namely 5 months before (and including) his first mention of COVID-19 and 5 months after. The first period extends from the 1st of September 2019 to the 31st of January 2020; the second period covers the period from the 1st of February 2020 to the 30th of June 2020. The corpora collected consist of 4215 tweets – 119 269 Tokens from which 8 730 are distinct. Due to the way data is exported from the online compiler tool, the corpora were saved in an Excel file. This proved useful for the organization of data, since the tweets were organized in single lines, improving visibility and making them more manageable for analysis and contrasting purposes.

The corpora were organized on different Excel pages: one page for the first period and another for the second period; subsequent corpus analysis was made on several different pages; as a result, the documentation and analysis were mechanical and systematic. The corpora, when collected, contained original tweets, tweets comprising just images or just links and also retweets. Because this research study aims to discuss Donald Trump’s pragmatolinguistic strategies, non-original tweets had to be discarded. This means that, before cleaning it, the corpora consisted of 9 682 tweets (4768 in Corpus 1 and 4914 in Corpus 2) and after cleaning it, the corpus totalled 4215 tweets (2136 in Corpus 1 and 2079 in Corpus 2).

Twitter’s privacy policies do not allow for “hydrated”¹⁰ tweets to be shared; therefore, one must refer to the tweet ID¹¹ to share a tweet¹² (Gold, 2020). This ensures that recipients of this data must go through Twitter’s API to “re-hydrate” tweets (Gold, 2020). This also prevents

¹⁰ Hydrated means a full tweet (copied and pasted in its entirety)

¹¹ The tweet ID functions as an identification number which is unique for every tweet.

¹² Pulling on Twitter’s developer-terms: "Individuals redistributing Tweet IDs and/or User IDs on behalf of an academic institution for the sole purpose of non-commercial research are permitted to redistribute an unlimited number of Tweet IDs and/or User IDs." – Retrieved from <https://developer.twitter.com/en/developer-terms/more-on-restricted-use-cases>

users from reading tweets which have been deleted from the platform (Gold, 2020). This does not affect sharing part of a tweet for analysis and all the tweet IDs are found in Appendix 1 and Appendix 2.

4.2.Data Filtering and Corpus Analysis

To filter and analyse the corpus, the study employed Wordsmith Tools 8. This software required the corpora to be in .txt format and cleaned of all non-words. This process was simplified using “search” and “substitute” in the list of options in Excel. Retweets were highlighted for instant removal and all non-words were replaced by a blank space.

Frequency sorting allowed for the most important part of further corpus analysis (two frequency lists were made, one for each time-period) because every section departed from extracting the most frequent nouns, adjectives, adverbs, pronouns and so on. From these wordlists, Wordsmith Tools 8 allows the creation of indexes¹³, which look similar to wordlists, yet enable the user to create clusters¹⁴, word clouds¹⁵, among other features.

In this study, corpus analysis entails two phases: one focused on Corpus 1 and another on Corpus 2. This is done to organize accurately the set of data during its presentation. Comparisons are made in the discussion section of Chapter 5. First, the nouns that have a frequency of at least 100 instances are extracted manually (*cf.* 5.1.1.) from the wordlist created for Corpus 1. Clusters are created out of these nouns to make it possible to observe them in the co-text¹⁶. These clusters are always explained through the use of concordance lines (Sinclair, 1999)¹⁷.

Concerning adverbs, the same process is followed and several adverbs are extracted. Lastly, all adjectives with a minimum frequency of 80 instances are extracted, that is so because

¹³ “One of the uses for an Index is to record the positions of all the words in your text file, so that you can subsequently see which word came in which part of each text. Another is to speed up access to these words, for example in concordancing.” – Retrieved from https://lexically.net/downloads/version8/HTML/uses_of_index_lists.html

¹⁴ A cluster is a small-set of words created around a keyword. In wordlists you can “ask for a word list consisting of two, three, up to eight words on each line.” – Retrieved from https://lexically.net/downloads/version8/HTML/wordlist_clusters.html

¹⁵ A word cloud makes it easier to identify patterns.

¹⁶ Ghadessy (1999) believes that the term co-text was introduced by Catford. Catford (1965:31) states: “By co-text we mean items in the text which accompany the item under discussion: hence co-textual”

¹⁷ Through a concordance line, one is able to “present a concordance display, and give you access to information about collocates of the search word, dispersion plots showing where the search word came in each file, cluster analyses showing repeated clusters of words (phrases) etc.”; “The point of a concordance is to be able to see lots of examples of a word or phrase, in their contexts.” – Retrieved from <https://lexically.net/downloads/version8/HTML/concord2.html>

it was relevant to have at least five adjectives for a sound research. These first steps are repeated for Corpus 2, yet differ in the collection of nouns, which is expanded (frequency wise) to reach the keyword coronavirus (89 instances), a noun which is relevant for the theme of this research. All data sets are stored and organized in Excel.

The second stage of corpus analysis aims at making feasible the goal of better understanding personal pronoun reference. As such, and similarly to the previous stages, the most frequent subject pronouns are extracted manually (*cf.* 5.1.2.) from Corpus 1 and clusters are created around them. At first, only the most frequent cluster is extracted, so as to give a general co-text to the use of pronouns, yet the complexity of personal pronoun shifts required further scrutinizing. This piece of research opted to extract the five most frequent clusters of each pronoun. The same steps are followed in the analysis of Corpus 2.

The third stage of corpus analysis reflects the value of information given around the pandemic. For this to be feasible the wordlists are triangulated with data extracted from the World Health Organization, so as to find all keywords related to COVID-19. This means that research is made in medical discourse to find all possible ways to name the virus, all symptoms, procedures and measures to be taken, as well as all the denominations of health workers in the forefront scenarios of the pandemic worldwide.

This piece of data is then searched for in the corpora. If found, it is extracted to inquire on its frequency and context of use. The same steps were applied to both corpora, and the sets of data are synthesised via clusters and concordance lines.

Finally, a decision was made to extract all vague expressions found in the corpora. To make this feasible, this research followed the steps laid down by past literature, which identified the vague expressions that were most commonly used by Trump in the 2016 debates. These expressions were: very, so, more, would, many, much, really, some, thing, millions, things, something, I think, a lot of (Parvaresh, 2017). Following the overall methodology, these expressions were extracted from Corpus 1 manually and organized by their frequency. Clusters and concordance lines were then created around the collected expressions. The same steps are followed for Corpus 2.

5. Data presentation, Synthesis and Analysis

In this chapter, this piece of research will expand on the corpora collected, by extracting and presenting the data relevant to the aims of the study. After a thorough presentation, the

focus will be on a contrastive analysis, between Corpus 1 and Corpus 2, aimed at uncovering the main pragmalinguistic differences and/or similarities. Particularly, this second section will discuss the data collected, the evidence of populist rhetoric, how COVID-19 can be seen as an opportunity (*cf.* crisis rhetoric, Chapter 3.2.2.), how the pronoun references occurred in Trump's Twitter, how the Gricean maxims were flouted and, lastly, how the audiences may have been affected by Trump's communication in Twitter.

5.1.Data Presentation and Research Findings

This first section of Chapter 5 is meant to introduce all the data extracted from both corpora. The data are divided in two parts, one concerning Corpus 1 and another concerning Corpus 2, i.e., the sets of data are presented separately at first; the data are only compared and discussed in the following section (*cf.* Chapter 5.2.). In short, this section is further divided into four parts, the first one concerns some content words, i.e., nouns, adverbs and adjectives, the second one focusing on personal pronoun reference (deixis), the third one looks at information given on the topic of COVID-19 and in the fourth a look is given to the use of vague expressions.

5.1.1. Nouns, Adverbs and Adjectives

5.1.1.1. Corpus 1

Frequency sorting allowed for the extraction of the 15 most frequent nouns out of Corpus 1, as seen in Table 1.

Nouns with a Frequency of at least 100 in Corpus 1		
Nouns	Frequency	%¹⁸
President	377	0,47%
Democrats	269	0,40%
Nothing	227	0,33%
Impeachment	210	0,31%
People	202	0,30%
Trump	158	0,24%
News	148	0,22%
Republican	130	0,19%
Country	128	0,19%
Schiff	126	0,19%
House	124	0,19%
American	118	0,18%
Time	118	0,18%
Years	115	0,17%
Party	105	0,16%

Table 1 – Nouns with a Frequency of at least 100, extracted from Corpus 1.

By observing Table 1, it is clear that the most frequent noun in Corpus 1 is *president*, which through clusters¹⁹ (cf. Table 2) and concordance lines²⁰ can be observed to be both self-referential (example 1) and employed to comment on foreign affairs, most commonly on Afghanistan (example 2) and Ukraine (examples 3 and 4). Not all nouns are represented in individual lines in Table 2, and that is so because the table focuses on clusters, which can be shared among frequent keywords. This can be seen with *nothing* and *democrats*.

¹⁸ “Frequency as a percent of the running words in the text” – Definition retrieved from <https://lexically.net/downloads/version8/HTML/wordlistdisplay.html?q=of+running+words>

¹⁹ Clusters are size 3 and have a minimum frequency of 3.

²⁰ Concordance lines are extracted with 80 characters, left and right collocates in Courier New size 8, as by default on Wordsmith Tools 8. Keywords are rendered in bold in the examples for easier identification.

Clusters Made out of the most Frequent Nouns in Corpus 1		
Clusters	Frequency	%
the president ²¹ of	33	0,05%
do nothing democrats	84	0,12%
the impeachment hoax	37	0,06%
the American people	28	0,04%
that president Trump	9	0,01%
the fake news	53	0,08%
the republican party	53	0,08%
of our country	22	0,03%
shift Adam Schiff	11	0,02%
the White House	29	0,04%
the same time	8	0,01%
for many years	9	0,01%

Table 2 – Following Table 1, the most frequent clusters of the nouns were extracted.

1. nothing. Illegal spying..... on the **President** of the United States.²²
2. or Taliban leaders and separately the **President** of Afghanistan were going to sec
3. a version of my conversation with the **President** of Ukraine that doesn't exist.
4. ON HIM BY ME. End of case! Again the **President** of Ukraine said there was NO

President is not the only instance of self-reference. It also happens through the use of the words *Trump* (example 5) and *Republican* (example 6). It is likely to be inferred from the collocational meaning that the former president tries to show that there was an imagined threat (MacWilliams, 2016), towards himself and his party. This is further supported by Trump's references to time and space, through *time* (example 7) and *years* (example 8), Trump pulled on audiences to remember the wrongdoings of the OTHER and the values that have been lost. As seen in most examples presented in this piece of research, the *country* (the United States) is a place under constant attack. Blankenship (2020) states that this is the perfect scenario to allow for building the binary notion of winners and losers.

5. nk God for a President like Donald J. **Trump** who will appoint judges like this. H
6. EMOCRATS ARE TRYING TO DESTROY THE **REPUBLICAN** PARTY AND ALL THAT IT STANDS FOR.
7. Bashar al-Assad our enemy. At the same **time** Syria and whoever they chose to help
8. ainst the European Union who has for many **years** treated the USA very badly on Tr

Further on, the co-text laid down by the clusters in Table 2 to observe the second most used noun, *democrats*. The noun shows signs of blame-shifting and vilification (Lacatus, 2019) of the opposition (examples 9 and 10), who is seen to be hurting the nation and the everyday *American* (example 11) that Trump was fighting for (example 12).

9. sequences! These Radical Left Do **Nothing Democrats** are doing great harm to our C
10. the House because of what the Do **Nothing Democrats** have done to our Country! You
11. American History! While the Do **Nothing Democrats** FAIL the **American People** and

²¹ Bold is used to highlight the noun inside the cluster. The same is done with concordance lines.

²² The double ellipsis found in this example shows how Trump connects two tweets, going over the limit of 280 characters, and signaling that his statement is not yet over.

12. nt our Country and fight hard for the **American People** while the Do **Nothing Democ**

The third most used keyword goes hand in hand with the second one, namely to the indefinite and compound *nothing*, Trump insulted the opposition and jeopardized their power and actions. Twitter is commonly used to comment on ongoing events, and so does Donald Trump, yet his comments were not just the occasional ones. His topics last over the course of several months, while replicating the tweets on the same subject, interlocutors become followers and truly believe in his point of view. The impeachment “hoax” (examples 13 and 14), a lexical item often occurring in his rhetoric, possibly showing that his disregard towards the establishment (Homolar & Scholz, 2019) cued up establishing a strong engagement with audiences (Anderson, 2017).

13. and energized in our fight on the **Impeachment** Hoax with the Do **Nothing Democrats**
 14. political investigations and the **Impeachment** Hoax! KEEP AMERICA GREAT! Thank yo

The *people* (examples 15 and 16), a common lexical reference in populist discourses (Hidalgo-Tenorio & Benítez-Castro, 2021), was expected to be frequent in Corpus 1. Trump used it to manipulate citizens into believing that he was the one to safeguard their values and best interests (Hidalgo-Tenorio & Benítez-Castro, 2021).

15. s Hispanics Asians & Women. More **people** working today than ever before. Rebu
 16. d be the end of a case run by normal **people!** - but not Shifty! Hit New Stock Mar

The information underneath follows the same procedures of the analysis of nouns. It focuses on adverbs having a minimum frequency of 100 instances. They are listed in Table 3: *not* (adverb of negation), *very* (adverb of degree), *just* (adverb of degree), *now* (adverb of time), *never* (adverb, indefinite frequency), *up* (adverbial particle) and *more* (adverb of degree).

Adverbs with a Minimum Frequency of 100 in Corpus 1		
Adverbs	Frequency	%
Not	256	0,38%
Very	248	0,37%
Just	210	0,31%
Now	188	0,28%
Never	186	0,28%
Up	179	0,27%
More	150	0,22%

Table 3 - Adverbs with a minimum frequency of 100 found in Corpus 1 (Before COVID outbreak 2019).

Following Table 3, it is interesting to note that the most used adverb by Trump, retrieved from Corpus 1, is the adverb of negation *not*, which can be used to threaten his enemies (example 17) or to defend Trump (example 18) and defend as well as praise his in-group (example 19), as perceived in the phrase-frames (*cf.* Table 4).

Clusters Made out of the most Frequent Adverbs in Corpus 1		
Clusters	Frequency	%
is not * ²³	8	0,01%
a very *	12	0,02%
just * the	13	0,02%
Democrats are now	6	n/a ²⁴
will never *	15	0,02%
made up *	11	0,02%
and * more	11	0,02%

Table 4 - Following Table 3, the most frequent clusters of the adverbs were extracted.

17. They will pay a very BIG PRICE! This is **not** a Warning it is a Threat. Happy New
 18. ump droned Soleimani...Plainly Trump is **not** a warmonger. He's a deal maker and
 19. ce Kavanaugh is a disgrace. This guy is **not** a good man he is a great man. He has

Trump's pragmatolinguistic strategies often include maximising or minimising events and people, namely, his actions which are always called *very* good, as observed in examples 20 and 21, *very* large, as evidenced in example 22 and *very* important, as is explicit in example 23. These actions are never limited and there is always much *more* to them (example 24). On the contrary, the actions of the out-group are always very big lies (example 25), perceived as definitely, leading to a *very* bad time for the United States (example 26). His enemy, as evidenced before, can take the form of the Democrats who are *now* "the party of high taxes" (example 27). This use of adverbs is intended to deconstruct prior assumptions on people, places and objects with a cognitive impact on interlocutors' future representations of reality.

20. s raises smoking age to 21! BIG! Had a **very** good talk with President Xi of China
 21. Impeaching the President for having a **very** good conversation with the Ukrainian
 22. d a better leaker! We have agreed to a **very** large Phase One Deal with China. The
 23. peach the Pres. Mississippi there is a **VERY** important election for Governor on N
 24. ls help for working families and much **more**. Over the last 3 years unemployment f
 25. ted to national security. This is a **very** big Lie. Read the Transcript! ...No
 26. being used by Nancy Pelosi. This is a **very** bad time for the United States Const
 27. AMERICA FIRST! #KAG2020 Democrats are **now** the party of high taxes high crime

The comments made by Trump about his enemies and the imagined threats he created to incite fear on citizens can be possibly inferred from the collocational meaning related to the adverb *never*. He tried to make the American citizen take action and protect his/her own nation (examples 28 and 29). Trump' enemy is accused of strategizing against the nation by making *up* accusations, by creating fake news (example 30) and setting *up* complex schemes which threaten Trump's leadership and destroy his image (examples 31 and 32). This is perhaps also an instance of blame-shifting. This so-called fraudulent party (as named by Trump) can be

²³ These are phrase-frames, i.e. "groups of wordgrams identical but for a single word", as defined by H. Fletcher in <http://www.kwicfinder.com/kfNgram/kfNgramHelp.html>. Phrase-frames are used here for a better picture of the context of use. The * can be replaced by several words, for instance "a very" is followed by big, important, good, bad and large

²⁴ n/a as in not available. WordSmith Tools 8 could not compute the percentage of running words for some results.

defeated by pulling on previous instances of the same issue to support his arguments (example 33), by forcing citizens to *just* read about it (example 34) or *just* by a third party acting appropriately (example 35).

28. ocrats truly knows it is. This should **never** be allowed to happen again! Thank yo
 29. ing corruption and propaganda. Should **never** be allowed to happen. Fake News!
 30. hiff a totally corrupt politician made **up** a horrible and fraudulent statement re
 31. f to find out why he fraudulently made **up** my phone call and read this.. ...fict
 32. hotel room for the evening or filling **up** a gas tank at an airport I do not own.
 33. demand his deposition. He is a fraud **just** like the Russia Hoax was and the Ukra
 34. oxNews The Democrats have gone Crazy. **Just** read the Transcript or listen to the
 35. ump said the Ukraine President should **just** do the right thing (No Quid Pro Quo).

The last part of speech under scrutiny in this section comprises adjectives. The aim is to understand how Trump used adjectives to modify his utterances and achieve his communicative goals. Adjectives chosen based on a minimum frequency of 80, so as to have at least five keywords. In Table 5 one might find: *great*, *big*, *new*, *good* (qualitative adjectives) and *wrong* (a classifying adjective).

Adjectives with a Minimum Frequency of 80 in Corpus 1		
Adjectives	Frequency	%
Great	440	0,66%
Big	167	0,25%
New	167	0,25%
Good	113	0,17%
Wrong	84	0,13%

Table 5 - Adjectives with a minimum frequency of 80 found in Corpus 1.

In Corpus 1, the most frequent adjective is *great*. Its occurrence may be expected due to its dissemination in mass media, often in a comic tone (same as *big* or any other overused adjective). Following the phrase-frame found in Table 6, *great* and its collocates “job”, “guy”, “governor”, “book”, “day” and “evening” can relate to actions, to people, to objects and even to intensify time references. Firstly, as previously evidenced, Trump comments positively on his own actions and those of his in-group (examples 36 and 37). Trump comments on *great* guys (example 38) and *great* governors (example 39), and even *great* books (example 40). It is worthwhile mentioning that books recommended by Trump often support his narratives and populist idealism. Depending on the co-text, Trump often has *great* days (example 41) and *great* evenings (examples 42), revolving around what he believes to be “good” or “bad” (a win-win relation).

Clusters Made out of the most Frequent Adjectives in Corpus 1		
Clusters	Frequency	%
a great *	59	0,09%
a big *	15	0,02%
New York *	32	0,05%
A very good	12	0,02%
did nothing wrong	17	0,03%

Table 6 - Following Table 5, the most frequent clusters of the adjectives were extracted.

36. this President busy. We're doing a **great** job on the economy we're building
37. ment! Senator Dan Sullivan is doing a **great** job for the people of Alaska while s
38. the edges sometimes but he is also a **great** guy and wonderful lawyer. Such a one
39. to pursue other interests. Rick was a **great** Governor of Texas and a great Secret
40. ion! Senator Rand Paul just wrote a **great** book The Case Against Socialism
41. r everybody. Proud of all! This is a **great** day for civilization. I am proud of t
42. isiana REPUBLICANS thank you for a **great** evening. Get out TOMORROW and VOTE REPU

Trump feeds the notion of winners and losers (Blankenship, 2020) by maximising the relevance of his gains. He does not win: he wins *big* (example 43) and his country wins with him (example 44). There are often comments about the ones he believes to be a loser, particularly the failing (example 45) and corrupt (example 46) *New York Times*²⁵. Although one would expect *wrong* to be used frequently as an insult, the adjective finds most of its use in defending Trump's actions, by often repeating that he "did nothing wrong" (example 47), since all that Trump does is in a very *good* way (example 48).

43. it is no point at a all (except for a **big** win for me!). The Democrats should ap
44. d be Impeached and worse! This is a **big** win for America and also for President
45. from day one. People at the Failing **New York Times** are very angry at him for hav
46. on Friday. Despite this the Corrupt **New York Times** used this poll in one of its
47. chment scam. I am not because I did nothing **wrong**. It is the other side including
48. trongly consider it! Just finished a very **good** and cordial meeting at the Whit

5.1.1.2. Corpus 2

Focusing now on Corpus 2, the extraction of nouns is not limited to those with a frequency of at least 100 instances and that is so because this research study intended to scrutinise the occurrence of the lexeme *coronavirus* and collocate "task force". There are 89 instances of this lexeme, as shown in Table 7.

²⁵ Although the automatic selection displayed *new* as a frequent occurrence in the corpus, "new" has also the role of noun modifier in the compound *New York Times*, acquiring a negative connotation because of the adjective "failing" and "corrupt" which are intentionally capitalized as if belonging to the compound noun *New York Times*.

Most Frequent Nouns in Corpus 2		
Nouns	Frequency	% ²⁶
People	232	0,39%
News	231	0,38%
Total	133	0,22%
Job	120	0,20%
Country	114	0,19%
Endorsement	114	0,19%
President	106	0,18%
States	106	0,18%
Joe	104	0,17%
Military	102	0,17%
State	97	0,17%
Nothing	96	0,16%
Democrats	95	0,16%
Coronavirus	89	0,15%

Table 7 – Most frequent nouns found in Corpus 2

Considering Table 7 and Table 8, the lexeme *president* is self-referential (example 49) and used to comment on both foreign affairs (examples 50 and 51) and local affairs (examples 52 and 53), with collocates related to Obama and the Chicago Police Union. *Nothing* modifies *democrats*, intended to undermine their power in the political scenario (example 54). The node *country* metaphorically stands for the victim, the object of threat to be performed by “the other” (examples 55 and 56).

Clusters Made out of the most Frequent Nouns in Corpus 2		
Clusters	Frequency	%
the people of	37	0,06%
the fake news	64	0,11%
complete and total	90	0,15%
a great job	26	0,04%
of our country	10	0,02%
and total endorsement	88	0,15%
president of the	9	0,01%
The United States	55	0,09%
Sleepy Joe Biden	19	0,03%
loves our military	22	0,04%
The great state	43	0,07%
do nothing democrats	32	0,05%
coronavirus task force	7	0,01%

Table 8 – Following Table 7, the most frequent clusters of the nouns were extracted.

49. Really Big Jobs Report. Great going **President** Trump (kidding but true)! THESE NU
50. ussia they say. But now they report **President** Putin wants Bernie (or me) to win.
51. ery good conversation by phone with **President** Xi of China. He is strong sharp an

²⁶ “Frequency as a percent of the running words in the text” – Definition retrieved from <https://lexically.net/downloads/version8/HTML/wordlistdisplay.html?q=of+running+words>

52. y! Did you hear the latest con job? **President** Obama is now trying to take credit
 53. er John Catanzara for being elected **President** of the Chicago Police Union. He al
 54. e constant criticism from the Do **Nothing Democrats** and their Fake News partners
 55. re has never been in the history of our **Country** a more vicious or hostile lamest
 56. y people being arrested all over our **Country** the Vandalism has completely stoppe

In Corpus 2 the lexeme *people* stands out as the most frequent noun used by Donald Trump, strengthening the populist discourses during the COVID-19 pandemic and showing the way he engages with generic and specific groups. The postmodifier marks the speaker’s distance from the referred group at the level of the utterance, such as the people of South Dakota (example 57), the people of Idaho (example 58) or the people of South Carolina (example 59), among many others. There might also be an inner interest to influence the citizens of these states in the elections. The manipulation of public perception is the overall theme of Corpus 2.

57. nson) is a phenomenal advocate for the **people** of South Dakota! He helped us deli
 58. s an incredible Representative for the **people** of Idaho! He fully supports the Bo
 59. a good friend and strong voice for the **people** of South Carolina. Heâ€™s helped u

Total and *endorsement* occur in utterances associated with overestimating the candidates Trump supports (example 60), all of which love the military, the farmers, the vets (veterans) and defend the border. “Complete and Total Endorsement” is repeated 88 times, part of an almost automated electoral utterance which often refers to the military, the border, the veterans and farmers. People endorsed by Trump do not get unique treatment and are all seen as a collective group supposedly sharing his ideals (examples 61 and 62).

60. Amendment trade Military and Vets. Wesley has my Complete and **Total Endorsement!**
 61. Low Taxes. Nancy has my Complete and **Total Endorsement!** November 3rd a big day
 62. Amendment. Chris has my Complete and **Total Endorsement!** Vote for Chris on June

By referring to *coronavirus* and *job*, Trump reinforces the idea that he is doing well and saving his country (examples 63 and 64). The coronavirus task force he devised is always active and they (example 65), his ingroup as well as himself are doing a “great job” by providing ventilators (example 66), testing (example 67) and mitigating the side effects of the virus (example 68). Anyone who spreads the opposite news is fake *news*, creating false narratives (example 69). Hence public discontent is reported to be influenced by the “lamestream” *media* perceived as corrupt (example 70), threatening the country and intending it to fail (example 71). Most blame is shifted towards his electoral opponent, *Joe Biden*, who is always insulted as “sleepy Joe” (a public offense) by Trump and often accused of wishing to destroy the nation (example 72).

63. n leading the counterattack on the **Coronavirus**. He feels they are doing very wel
 64. m the great job he is doing on the **CoronaVirus** Task Force. He has the total conf
 65. be met with serious force! We did a great **job** on CoronaVirus including the very
 66. UT LACK OF TAKERS.â€ We have done a great **job** on Ventilators Testing and everyt

67. repeat when he knows we have done a great **job** on Testing just like we have on
 68. DC and my Administration are doing a GREAT **job** of handling Coronavirus including
 69. I haven't heard one member of the Fake **News** Establishment even mention this
 70. 9 t etc. and the CoronaVirus. The Lamestream **Media** is corrupt and sick! What i
 71. can sterilize masks quickly. The Lamestream **Media** wants us to fail. That will N
 72. as I have for the past 3 years. Sleepy **Joe** Biden will destroy both in very short

Interestingly, the most frequent adverbs retrieved from Corpus 2 are the same as in Corpus 1 yet, they differ both in order of frequency and co-text, as can be observed in Tables 9 and 10.

Adverbs with a Minimum Frequency of 100 in Corpus 2		
Adverbs	Frequency	%
Very	225	0,37%
Not	210	0,35%
Just	165	0,27%
Now	153	0,25%
More	151	0,25%
Up	141	0,23%
Never	105	0,17%

Table 9 - Adverbs with a minimum frequency of 100 found in Corpus 1.

Following Tables 9 and 10, the order of data presented echoes that of Corpus 1. The adverb *not* is frequently used for promises by modifying the modal verb will (examples 73 and 74).

Clusters Made out of the most Frequent Adverbs in Corpus 2		
Clusters	Frequency	%
a very *	22	0,04%
Will not be	13	0,02%
just spoke to	9	0,01%
we * now	8	0,01%
more than * ²⁷	11	0,02%
up * great	8	0,01%
will never *	17	0,03%

Table 10 - Following Table 9, the most frequent clusters of the adverbs were extracted.

73. of those very brilliant Voters. You will **not** be disappointed! Good numbers comin
 74. ...Federal Government. A quarantine will **not** be necessary. Full details will be

The intensifier *very* relates to actions that are *very* good (example 75) and very successful (example 76), while also intensifying victories (example 77), yet, the intensifier *very* also plays a role in creating fear, when associated with COVID-19, the so-called “gift” from a foreign nation (example 78). In Corpus 2, *more* magnifies the successes by Trump, everything is done better and more than in any other country (example 79) and sometimes better than in all countries in the world “combined” (example 80).

²⁷ The keyword is more often used as an adjective in the co-text.

75. e Virus very seriously and have done a **very good** job from the beginning including
76. ident Xi strongly leads what will be a **very** successful operation. We are working
77. that. The only person that can claim a **very** big victory in Iowa last night is
78. ! All over the World the CoronaVirus a **very** bad gift from China marches on
79. the U.S. because we are testing far **more** than any other country and ever expandi
80. 11 million tests and going up fast. **More** than all countries in the world combine

This seems to be a strategy to minimize the severity of COVID-19 striking the United States by intentionally avoiding the allusion to the ineffective management of the crisis, because the former president often stated that “the other” (intentional distance) was doing much worse. The same strategy is evidenced through the lexical item *now*, which is used, almost identically, to show how Trump’s leadership placed the United States above other countries (examples 81 and 82). Trump further tried to prove his leadership by mentioning his communication with several other international presidents (example 83), all of which were reported to be his friends. This transmitted a sense of immediacy, since he tweeted *just* after speaking to these individuals.

81. e after having been left little we are **now** doing more testing than all other cou
82. needing a Ventilator got one! We have **now** Tested more than 5 Million People. Th
83. fighting hard against CoronaVirus! **Just** spoke to my friend President Joko Widodo

Trump presented himself as a saviour of the nation, and often promised that he would not let the actions by other parties or by other nations affect the wellbeing of the United States. He went as far as promising that he would *never* let his citizens down (examples 84 and 85). He also declared that his opponents would *never* be allowed to make the country a communist one (example 86) and that their reputation would *never* be the same (example 87). Trump further indicated that those whom he endorsed should “keep *up*” the great work (example 88), giving the impression that they had always been doing a “great work” by, for instance, opening *up* their “great country” (example 89).

84. n the handling of the Pandemic. We will **never** let the great U.S. Oil & Gas I
85. s we no longer have our freedom. I will **never** let it happen! They tried hard in
86. ld be a total disaster and the USA will **never** be a Communist Country!
87. k and lonely path! Your reputation will **never** be the same! Coronavirus: In addit
88. nue to build more hospitals/beds. Keep **up** the GREAT WORK! Will be starting The W
89. haps like never before!!! Once we OPEN **UP** OUR GREAT COUNTRY and it will be soone

It is evidenced in Table 11 that Corpus 2 shares the bulk of its most frequent adjectives with Corpus 1. This likely means that Trump’s expressions were repetitive in their form, yet potentially not in their use. There is a new adjective retrieved from the corpus: *strong* (a qualitative adjective).

Adjectives with a Minimum Frequency of 80 in Corpus 2		
Adjectives	Frequency	%
Great	515	0,85%
Big	145	0,24%
New	140	0,23%
Strong	97	0,16%
Good	96	0,16%

Table 11 - Adjectives with a minimum frequency of 80 found in Corpus 2.

With Table 12 in mind (cf. Table 11), it is possible to infer the extent to which these adjectives follow an electoral tone, which focused on the people that Trump endorsed for the elections. For instance, the adjective *great* elevated good actions (example 90), people (example 91, 92 and 93), objects (example 94) and periods of time (example 95).

Clusters Made out of the most Frequent Adjectives in Corpus 2		
Clusters	Frequency	%
a great *	80	0,13%
a big *	17	0,03%
New York * ²⁸	26	0,04%
strong on	43	0,07%
a very good	7	0,01%

Table 12 - Following Table 11, the most frequent clusters of the adjectives were extracted.

90. ust the opposite. Our team is doing a **great** job with CoronaVirus! Someone needs
91. Lose. The Pastor is a winner and a **great** guy. Much can be learned from him. B
92. very much to Ken Langone for being a **great** American and for your wonderful comm
93. Makes no difference we already have a **GREAT** Senator! Twitter Pulls Trump Campaig
94. ur Country and our Flag? Actually a **great** book by a great and highly respected
95. week for many people of Faith and a **great** day to lift our voices in Prayer. I w

In Corpus 2 the adjective *big* is often linked with price (example 96), which exposed how vague “they” had to pay the nation for some action of which they were accused of by Trump. *Big* can also occur when Trump endorsed his party for the elections, particularly in the premodifying position in the noun phrase form “big Tax Cutter” (example 97).

96. They along with others should pay a **big** price for what they have purposely done
97. Tom has deep roots in Wisconsin is a big Tax Cutter and will help me DRAIN THE

This is further evidenced in the use of the adjective *strong*, which is tied with the so-called good values of his party. This party was *strong* on the border (example 98), *strong* on crime (example 99) and *strong* on life (example 100). *Strong*, as used by Trump in the tweets retrieved from Corpus 2, seemed almost like part of an automatic response, used to describe any member of his political party. As a result of this strategy there is no degree of differentiation in the utterances produced to publicize his endorsement of other politicians.

98. rans Supports Small Business and is **Strong** on the Border and Second Amendment...

²⁸ Cf. note 25

99. or Congress in Minnesota. Nicole is **Strong** on Crime and Borders Cutting Taxes yo
 100. a champion for West Virginia! He is **strong** on Life and the Second Amendment and

5.1.2. Personal Pronoun Reference

This subsection intends to have a look at the use of first-person pronouns (singular and plural), second-person pronouns (singular and plural) and third-person pronouns (singular and plural). These are found to create indexical expressions in most of the studies reviewed in the literature, since several groups can be indexed through a reference to the personal pronoun *we* (supposedly reinforcing ingroup relations) or the personal pronoun *they* (likely to exclude a group of interlocutors referred as outgroup).

5.1.2.1. Corpus 1

Concerning the subject pronouns, the five most frequent ones were extracted from both corpora. The pronouns that belong to Corpus 1 were organized in the following table:

5 most Frequent Subject Pronouns in Corpus 1		
Pronouns	Frequency	%
I	550	0,82%
They	450	0,67%
You	434	0,65%
We	344	0,51%
He	311	0,46%

Table 13 - The 5 most frequent subject pronouns found in Corpus 1

In accordance with the same procedures devised for the previous sub-sections, one can observe the use of each of these pronouns. This is further made possible by working out their meaning potential from the corresponding phrase-frames, found in Table 145. Additionally, scrutinising these pronouns may allow for the understanding of the context as well as discern between their possible indexical expressions.

Clusters Made out of the most Frequent Pronouns in Corpus 1		
Clusters	Frequency	%
I will *	26	0,04%
They are *	20	0,03%
Thank you * ²⁹	64	,10%
We are *	41	0,06%
He is *	27	0,04%

Table 14 - Following Table 13, the most frequent clusters of the subject pronouns were extracted.

²⁹ When speaking about "I thank you.", there is an explicit indication of the subject-verb-object structure in English. Yet, "thank you" has been used as an elliptical sentence also acquiring the function of an idiomatic expression (further research results can be compared to the ones occurring with the verb "thank" and collocates in the British National Corpus available at <https://www.english-corpora.org/bnc/>, and the Corpus of American English). Also see the discussion on phrase -frames on table 17 (underneath).

Regarding Corpus 1, the use of the syntactical construction *I will* denotes a promise made towards the future. These various promises can be either new (example 101) or repeated (example 102). This second type of promise alludes to actions that Trump acknowledges he has been doing tirelessly.

101. th us. Captured ISIS prisoners secured. **I** will be making a statement at 11:00 A.
 102. years will become the best ever by far. **I** will always protect your Pre-Existing

Through the pronominal scale for political reference (Rees, 1983:16) one can observe that the pronoun reference *you* (generic pronoun reference) belonging to the phrase “thank you” (also having the function of noun as in a thank you note in examples 104 and 105) seemed to be used regularly to express gratitude towards groups of people in general (example 103) and specific individuals (example 104 and 105). It could also be used as a resource for Trump to acknowledge his own actions (example 106)

103. t to raise and way too slow to cut! Thank **you** to House Republicans for being tou
 104. popular individual mandate for you! Thank **you** to Rick Scott. This Impeachment Ho
 105. d NATO spending increased by \$130B! Thank you to President Zelensky. Case over.
 106. hat the U.S. is finally responding (thank **you** President Trump). This is taking..

The first-person plural pronoun *we* is continually employed to make reference to the efforts of Trump’s in-group. This is carried out both in the present (examples 107 and 108) and in the future (example 109). These utterances take the form of promises.

107. ol and we save our small refineries! **We** are doing very well in our negotiations
 108. and to their very fragile currency. **We** are helping the Kurds financially/weapon
 109. gton establishment and with your help **we** are going to complete the mission and

The pronoun *he* can be used to praise (examples 110 and 111) and to insult (example 112 and 113). This happens by resorting to adjectives in the co-text around the third-person singular.

110. strong supporter of our #MAGA Agenda. **He** is strong on the Second Amendment and
 111. ean Spicer on Dancing with the Stars. **He** is a great and very loyal guy who is wo
 112. eading it to Congress as though mine! **He** is sick! All the Do Nothing Democrats

Lastly, in this initial analysis, the third-person plural *they* reproduces the same results as the ones with the pronoun *we*. This parallelism is found in the way Trump comments on actions performed both in the simple present (example 114) and in the future forms (example 115) tenses – often by strongly criticising imagined threats and alleged schemes (example 116).

113. are afraid to even walk the streets. **He** is a terrible mayor who should stay out
 114. hing Democrats pay a price for what **they** are doing to our Country and when do
 115. Democrats have just announced that **they** are going to seek to Impeach me over NO
 116. y other of their Witch Hunt schemes **they** are trying to start one just as ridicule

The potential for indexicality can be observed in the co-text of pronouns. Henceforth, the analysis aims at further contextualizing the use of every pronoun collected above by expanding on more than a single phrase-frame. Following Table 15, one can observe the different phrase-frames of the first person-singular *I* on Corpus 1

Phrase-frames of <i>I</i> in Corpus 1		
Phrase-Frames	Frequency	%
I will *	26	0,04%
That I *	20	0,03%
I have *	20	0,03%
I * nothing	15	0,02%
I don't *	13	0,02%

Table 15 - Phrase-frames of *I* in Corpus 1.

Unsurprisingly, the pronoun *I* is tied with Trump himself. Therefore, it lays the ground for the breakdown of other pronouns which might be more prone to ambiguity. Observing the occurrence of the pronoun *I* in context, one can recognize it is used for promises, as previously observed (examples 117 and 118), and also used to insult his followers' skills (example 119). Moreover, it is employed to remind others about the past (example 120).

- 117. recent past more like the Old Days. **I** will be meeting with the Vice Premier tod
- 118. rs will become the best ever by far. **I** will always protect your Pre-Existing Con
- 119. his is anybody dumb enough to believe that **I** would say something inappropriate
- 120. three years ago today January 20 2017 that **I** was sworn into office. So appropria

The pronoun *I* can also be associated with tweets used for criticism, oftentimes targeted at groups said to be mistreating Trump (examples 121 and 122), or otherwise as a means to protect face by disclaiming guilt (example 123) and detaching himself from others (example 124). Lastly, Trump plays the role of ignorant, remarking that he does not know about the transgressions that he is accused of having committed (examples 125 and 126) by the opposition and reported by the mainstream media.

- 121. ay would be able to see how unfairly **I** have been treated and that this is indeed
- 122. rs of patrolling our Southern Border **I** have never seen Mexico act like a true Bo
- 123. d.... ...lawyer has already stated that **I** did nothing wrong. John Bolton is a pa
- 124. t must end NOW. So bad for our Country! **I** WANT NOTHING! Today I opened a major
- 125. blican!absolutely no pressure. **I** don't know of any crime that was commit
- 126. r Trumper Diplomat Bill Taylor (who **I** don't know) in testimony before Congress

The first person-plural form *we*, offered in Table 16, can be seen to transmit several indexical references. First, it is employed to associate Trump with his administration or party. Second, it can be used to link Trump to citizens. Third, it can connect Trump with the country. Ultimately, the pronoun *we* can mean Trump himself or it can mean someone else, a reference

which is found through quotation. This interpretation is expanded in the utterances displayed underneath.

Phrase-frames of We in Corpus 1		
Phrase-Frames	Frequency	%
We are *	41	0,06%
We will *	23	0,03%
We have *	14	0,02%
And we *	13	0,02%
That we*	8	0,01%

Table 16 - Phrase-frames of We found in Corpus 1.

Recapitulating, Trump employs the pronouns *we* to correlate himself and his party. In this indexical position, Trump was fighting for his country and together they were winning (example 127), keeping America great (example 128) and helping foreigners (example 129). Trump presents himself as a winner, who acts in a group, i.e., the Republicans (example 130).

127. we are going to keep on fighting and **we** are going to keep ON WINNING! We are ON
 128. nothing but stymie all of the things **we** are doing to Make America Great Again.
 129. and to their very fragile currency. **We** are helping the Kurds financially/weapon
 130. re witnessing here - a lynching. But **we** will WIN! Thank you Republicans. 185 ou

The second interpretation of the pronoun *we* and its collocates established a link between Trump and the citizens – which he claimed to be part of. He remarks that he works with the people, united under the same goals (example 131). He also conveys that citizens are missing beneficial opportunities (example 132) because they are listening to the lies of “the other” – the enemy (example 133).

131. Mexico with Great American Patriots! **We** are all united by the same love of Coun
 132. once in a lifetime opportunity that **we** are missing because of Boneheads in a hy
 133. ff been fully discredited by now? Do **we** have to continue listening to his lies?

The third decoded meaning translates into an affiliation between Trump and the country as the one and only. In this scenario the country is the number one in “the Universe” (example 134) and has the best experts (example 135)

134. ack to the United States of America! **We** are now NUMBER ONE in the Universe by F
 135. to monitor the ongoing developments. **We** have the best experts anywhere in the w

Fourth, there are some instances where the plural form of the subject pronoun *we* is used to replace the singular form *I*. Therefore, most mentions of winning are understood as Trump believing himself to be a winner in the battles against his enemies (Blankenship, 2020) – this is evidenced in examples 136 and 137. This linguistic manipulation also serves the purpose of hiding the way Trump himself feels attacked by the media (example 138). He

appears shocked because he believes himself to be fighting for Americans (example 139) and for the nation (example 140).

136. Corrupt...The good news is that **we** are winning. Our real opponent is not th
 137. I get bored of telling you that and **we** will never get tired of winning! Congres
 138. y. We get ZERO media credit for what **we** have done and are doing but the people
 139. tate in defending American lives and **we** will never stop working to defeat Ra
 140. pe you won't need it! The truth is that **we** have a nation that is disgusted wit

Lastly, there is a scenario where the first-person plural *we* does not include Trump, as in example 141. This is possible because Trump often cited his opposition to create an argument. This reading of the pronoun may be partly associated with the country, the citizens or an unknown third party.

141. dent Trump is a danger to our nation and **we** must move quickly. They didn't get

Considering Table 17, the focus is switched to the second-person singular *you*, which is claimed to stand in the middle of the pronominal scale by Rees (1983). First and foremost, the pronoun is intended to address specified individuals – as explicit in examples 142, 143 and 144 – and to approach specific groups in the establishment – as seen in example 145.

Phrase-frames of You in Corpus 1		
Phrase-Frames	Frequency	%
Thank you *	64	0,10%
See you *	15	0,02%
You to *	7	0,01%
If you *	6	n/a
You * the	6	n/a

Table 17 - Phrase-frames of You found in Corpus 1.

142. or Evangelicals or religion itself! Thank **you** to Franklin Graham for stating th
 143. d NATO spending increased by \$130B! Thank **you** to President Zelensky. Case over.
 144. ed during the Trump Administration. Thank **you** to Iran on a very fair negotiatio
 145. of law enforcement and security. THANK **YOU** WORKING HARD!

The pronoun can also be used to connect with the entire population of a state (examples 146, 147 and 148). It performs in a manner that unifies the people, forming a group that acts under the mind of Trump.

146. Louisiana it is really important for **you** to go out and vote on October 12th for
 147. k Times! On my way to New Mexico see **you** all shortly at the @StarCenter! #KA
 148. o are already on site. We are with **you** all the way North Carolina. BE SAFE! Jus

One can also perceive the way the second person pronoun *you* can become unclear for the hearer/interlocutor in its interpretation. It can be adopted to make contact with all citizens individually (examples 149 and 150). In this form, one can interpret the pronoun as a tool to link Trump to the individuals, whom he wanted to influence (example 151). Nonetheless, the second person singular can be ambiguous, without a clear referent or pragmatic goal. In this

indexical position it can mean anyone and everyone (example 152). It coincides with the assumption of a generic reference.

- 149. losi and the Radical Left Democrats. See **you** on Monday night VOTE TUESDAY!!!
- 150. for Governor on November 5th. I need **you** to get out and VOTE for our Great Repu
- 151. looking at the people of Louisiana. If **you** want to defend your values your jobs
- 152. ME!BUT THE BEST IS YET TO COME! If **you** listened to the flawed advice of @p

Drawing on Table 18, one can observe the third-person singular *he*. In Corpus 1 the pronoun seems to be aimed at specific individuals, ranging from friends (example 153), to in-group members (examples 154, 155, 156, 157 and 158).

Phrase-frames of He in Corpus 1		
Phrase-Frames	Frequency	%
He is *	27	0,04%
He will *	12	0,02%
He has *	10	0,01%
He loves our	10	0,01%
That he *	8	0,01%

Table 18 - Phrase-frames of He found in Corpus 1

- 153. d a great Secretary of Energy....**He** is also my friend! At the same time I
- 154. nt for Virginia Senate 13th District. **He** is strong on Crime the Border our Mili
- 155. for the outstanding job he has done. **He** will be leaving at the end of the year
- 156. have worked with Tony for 3 years - **he** will do a fantastic job! Thank you to Da
- 157. ote for Tate Reeves on November 5th. **He** has my Complete and Total Endorsement!
- 158. is Strong on Crime and the Border **he** Loves our Great Vets and Military....

The personal pronoun subject *he* can also be used to implicate Trump’s enemies/opponents (example 159) functioning as a way for Trump to protect face (example 160). Lastly, this research found instances of the pronoun form *he* as self-referential. Echoing what was analysed beforehand, this indexical reference is possible because of Trump’s use of citation, as observed in example 161.

- 159. n the no name Senator from Maryland. **He** has been on forever playing up the Impea
- 160. it up! The President of Ukraine said that **he** was NOT pressured by me to do anyth
- 161. President I’ve seen in many years. **He** is going to do what is good for America

Finally, a brief look is given at the different indexical references associated with the third person pronoun reference, *they* (cf. Table 19). Through the analysis of the data, it is disclosed that the prevailing group being replaced by the pronoun are the Democrats. This notion is largely evidenced in the examples below.

Phrase-frames of They in Corpus 1		
Phrase-Frames	Frequency	%
They are *	20	0,03%
They don't *	16	0,02%
They have *	13	0,02%
They * the	12	0,02%
And they *	11	0,02%

Table 19 - Phrase-frames of They found in Corpus 1

The Democrats are seen as insane (example 162) because Trump framed them as wanting to impeach him by all necessary means (examples 163, 164, 165 and 166). Trump believed they did so because they did not care about the nation (example 167).

162. ical Left Democrats were sane which **they** are not it would be case over! The D
163. Democrats have just announced that **they** are going to seek to Impeach me over NO
164. ats when you know that this is what **they** are doing with their majority. Their c
165. y other of their Witch Hunt schemes **they** are trying to start one just as ridicu
166. the Democrats. It is so wrong but **they** don't even care anymore. They have gone
167. stop this ridiculous impeachment! **They** don't have a clue but I do. The USA is

The personal pronoun *they* can also be employed to embody past administrations (example 168) or to refer to “fake news” media for writing “whatever” (example 169) and never talking about the good job Trump did (example 170).

168. st Wars are still pushing to fight. **They** have no idea what a bad decision they
169. anymore they just write whatever **they** want! The story in the Amazon Washing
170. hat this Administration has done. **They** don't talk about the great economy the

Then, the personal pronoun *they* can also be used to mention American soldiers in foreign ground (example 171) or European countries and their interests (example 172). Lastly, the pronoun can be used as a strategy to spread non-factual information and be ambiguous (example 172).

171. aining in that section of Syria and they have been removed any unforced or unne
172. ean countries helping Ukraine more? **They** are the biggest beneficiaries. Why is
173. l with Ukraine. Fiction! ...And **they** say you can add 7% to 10% to all Trump num

5.1.2.2. Corpus 2

This subsection offers the same procedures devised in the previous one. The 5 most frequent personal pronouns are extracted from Corpus 2 and are displayed in Table 20. This analysis will start by outlining the most common co-texts (through the most frequent phrase-frames) and will then scrutinise on subject pronouns individually.

5 most Frequent Subject Pronouns in Corpus 2		
Pronouns	Frequency	%
I	528	0,88%
You	483	0,80%
They	402	0,67%
We	379	0,63%
He	337	0,56%

Table 20 - The 5 most frequent subject pronouns found in Corpus 2.

Observing Table 21, it is clear that Corpus 2 has the same phrase-frames as Corpus 1, yet due to belonging to different periods, their meaning can differ.

Clusters Made out of the most Frequent Pronouns in Corpus 2		
Clusters	Frequency	%
I will *	45	0,07%
Thank you *	93	0,15%
They are *	36	0,06%
We are *	44	0,07%
He is *	40	0,07%

Table 21 - Following Table 20, the most frequent clusters of the subject pronouns were extracted.

The subject pronoun *I* is used to make promises. These can range from a promise to perform a new action (example 174), to a promise to keep performing an action (example 175) and to a promise never to perform an action (example 176). Evidenced in these examples is a shift in the speech act of promising.

174. of thousands of complex Ventilators! **I** will be having a White House Press Confer
 175. crats to come together and VOTE YES! **I** will always put.... ...the health and we
 176. e fighting hard against CoronaVirus! **I** will never let our Post Office fail. It

The second-person pronoun *you*, serves the purpose of showing gratitude towards groups of people (example 177), people in specific (example 178) and as a means for Trump to claim credit to himself (example 179).

177. faster than currently anticipated. Thank **you** to all of those who worked with me
 178. rence today at 5:30 P.M. Thank you! Thank **you** to William Perry Pendley of the Bu
 179. Failed presidential candidate (thank **you** President Trump!) Carly Fiorina said sh

The personal pronoun plural form *we* is found in utterances which comment on the actions related to the in-group, both in the present (examples 180 and 181) and in the future tense (example 182).

180. and beds and soon the great things **we** are doing on testing. People are really
 181. remain open for you no matter what. **We** are working hard to remove any barriers
 182. for your continued support. Together **we** are going to KEEP AMERICA GREAT! #BlackV

The third person pronoun *he* is explicit in utterances which aim at praising (example 183) or paradoxically insulting (example 184).

183. nager over made up nonsense. Actually **he** is doing a great job I never shouted at
 184. t don't worry we will win anyway!). **He** is a disaster for America and for the G

Lastly, the occurrence of the pronoun *they* parallels the one by the plural *we*. That is possibly so because it is employed in utterances in which the speaker comments on the action in the present (example 185) and in the future (example 186), yet focused on “the other”. It is also exploited to imply that “the other” is a threat for the nation (example 187).

185. Sanders fat ahead of schedule. Now **they** are doing everything possible to be nic
 186. oxandfriends Regulate Twitter if **they** are going to start regulating free spee
 187. s response except in the Fake News. **They** are a disgrace to America! Dems are try

In Corpus 2 (Table 22) the first-person pronoun *I* occurs in utterances underpinned by the locutors reference to promises, as seen in examples 188 and 189. In some instances, it was used by Trump to show the way others were blocking his policies (example 190). He further commented that his endeavours made his enemies go crazy (example 191) and he forced the opponents to learn about his successful outcomes despite the pandemic (example 192).

Phrase-frames of I in Corpus 2		
Phrase-Frames	Frequency	%
I will *	45	0,07%
I * be	41	0,07%
I am *	16	0,03%
That I *	13	0.02%
I was *	12	0,02%

Table 22 - Phrase-frames of I found in Corpus 2.

188. ominee may be please understand that **I** will be working hard with Steve all the
 189. an previous but it is still no good. **I** will ALWAYS PROTECT PEOPLE WITH PRE-EXIS
 190. conomy Jobs Military Vets 2A and more **I** would be at 70%. Oh well what can you
 191. crats have gone absolutely crazy that **I** am doing daily Presidential News Confer
 192. money will aid in economic recovery! **I** am proud to announce the Portland Areaaâ€

Trump also reported on what he believed to be fake news (example 193). Then he praised himself (example 194) and reminded the reader about the past mistakes of his opponents (example 195). He did so to claim that acting against the opponents was the correct resolution (example 196).

193. hear that Fake News CNN just reported that **I** am isolated in the White House won
 194. d know the history of our Country say that **I** am the hardest working President i
 195. oll well as mayor in handling crisis! **I** was criticized by the Democrats when I
 196. s slow in reacting to Covid 19. Wrong **I** was very fast even doing the Ban on Chi

Concerning the first-person plural, the data are offered in Table 23.

Phrase-frames of We in Corpus 2		
Phrase-Frames	Frequency	%
We are *	44	0,07%
We will *	39	0,06%
We have *	22	0,04%
We * be	16	0,03%
Together we *	13	0,02%

Table 23 - Phrase-frames of We found in Corpus 2.

First, there are some instances in which Trump commented on how well he and his in-group were working (examples 197 and 198). Then, there are instances in which Trump made promises to help others in the name of the country (example 199). There is also an occurrence of the personal pronoun reference *we* that associates Trump with several congressmen, as shown in example 200.

197. g great reviews finally for how well **we** are handling the pandemic especially ou
198. thousands and we have many to spare. **We** are helping other countries which are d
199. n Moreno of the Republic of Equador. **We** will be sending them desperately needed
200. ueSenate... Great work @RepChipRoy together **we** are keeping AMERICAN WORKERS emp

Some occurrences of the pronoun *we* reinforce the implicit reference to Trump and citizens being together, working together to help the country (examples 201, 202 and 203) stay strong and prevail. The actions needed to keep America safe are performed by the collective as emphasized in the utterances evidencing the use of the personal pronoun *we*, entailing Trump and the nation. In his own bearings, the nation was doing more than every other country (example 204), working together against the virus (example 205), along with enduring all the suffering as the outcome of the pandemic (example 206).

201. for your continued support. Together **we** are going to KEEP AMERICA GREAT! #Black
202. eople want to get back to work ASAP. **We** will be stronger than ever before! I he
203. N of our citizens. Strong and United **WE** WILL PREVAIL! Today I spoke with Americ
204. kewise after having been left little **we** are now doing more testing than all oth
205. his as a time of unity and strength. **We** have a common enemy actually an enemy o
206. hree days in memory of the Americans **we** have lost to the CoronaVirus....On

There are instances in which the plural reference *we* is used instead of the singular *I*. These utterances were focused on winning over some enemy (examples 207 and 208). Additionally, there is an instance in which Trump protects face and avoids commitment by expressing his opinion through the cover of a collective voice instead of a singular one (example 209).

207. t. Just like 2016 but worse. Sad but **we** will win big! If you watch Fake News @C
208. difficult to win (But don't worry **we** will win anyway!). He is a disaster for
209. witter has now shown that everything **we** have been saying about them (and their

As can be accounted in Table 24, the pronoun reference *you* is explicit in utterances that express gratitude (example 210) and support towards specific people (example 211). On

the contrary, the pronoun is also found in utterances that insult individuals (example 212). Likewise, the pronoun could be employed to refer to countries (example 213), citizens of a specific state (example 214) as well as groups in the government (example 215).

Phrase-frames of You in Corpus 2		
Phrase-Frames	Frequency	%
Thank you *	93	0,15%
You to *	18	0,03%
You * a	11	0,02%
You have *	8	0,01%
You are *	7	0,01%

Table 24 - Phrase-frames of You found in Corpus 2.

210. OTE for Steven tomorrow March 10th! THANK **YOU** Jim for your incredible support o
 211. of the Great State of Oklahoma and **you** have my Complete and Total Endorsement!
 212. Nancy Pelosi you are a weak person. **You** are a poor leader. You are the reason
 213. closer cooperation between friends. Thank **you**, India and the Indian people, for
 214. y a lot. Also 97% Plus of the vote! Thank **you** Iowa! Market up big today on very
 215. @VP and the CoronaVirus Task Force. Thank **you**! The BEST decision made was the t

In Corpus 2, Trump uses the pronoun *you* to address online followers, praised for being “keyboard warriors” (example 216), to acknowledge veterans (example 217) and to greet citizens in general (examples 218 and 219). The pronoun can further be used as a generic reference to address anyone and everyone (example 220). In spite of that, the most interesting use occurs when Trump congratulates himself, as evident in example 221.

216. ery coll Thank you. My great honor! Thank **you** to all of my great Keyboard Warri
 217. to all of our Vietnam era Veterans. **You** have earned our gratitude and thanks by
 218. in Faith Family God and Country. Thank **you** for a beautiful evening! #KAG2020
 219. oronaVirus doesn't care what party **you** are in. We need to protect ALL American
 220. Now it is much more corrupt and what you are seeing is the least of it...but W
 221. n. Likewise Minneapolis was great (thank **you** President Trump!). Congressman And

In Corpus 2 (following Table 25) the third-person pronoun *he* gains an electoral tone. It is often employed to address party members whom Trump likes and endorses (examples 222,223,224,225 and 226). The pronoun also occurs in utterances that aim at insulting individuals Trump dislikes (examples 227, 228 and 229), a clear threat to interlocutors’ positive face (Brown & Levinson, 1987).

Phrase-frames of He in Corpus 2		
Phrase-Frames	Frequency	%
He is *	40	0,07%
He will *	22	0,05%
He * a	17	0,03%
He * our	13	0,02%
And he *	10	0,02%

Table 25 - Phrase-frames of He found in Corpus 2.

222. n to be the National Press Secretary. **He** is a strong loyal and trusted member o
 223. tter VOICE than Senator @SteveDaines. **He** is doing an incredible job! Whoever th
 224. a GREAT job for the People of Ohio! **He** will always Protect your #2A Defend our

225. to help us Make America Great Again! **He** will Fight for Small Business supports
 226. tah) is a tremendous fighter for Utah. He served our Country in the U.S. Air Fo
 227. about him and many others agree. Glad **he** is gone! Probably the only thing Barac
 228. rous Middle East Wars just announced **he** will be voting for another stiff Sleepy
 229. taxes and weaken our Great Military. **He** is a puppet... ..of Schumer and Pelos

Lastly, following Table 26, the pronoun reference *they* in the utterances analysed is linked to the democrats (examples 230, 231 and 232) and to the previous U.S. administration (example 233). Both parties are claimed in Trump’s words to have acted against the nation and its president for personal benefit.

Phrase-frames of They in Corpus 2		
Phrase-Frames	Frequency	%
They are *	36	0,06%
They were*	12	0,02%
They * doing	12	0,02%
What they *	11	0,02%
They will *	11	0,02%

Table 26 - Phrase-frames of They found in Corpus 2.

230. ey tried hard in 2016 and lost. Now **they** are going absolutely CRAZY. Stay Tuned
 231. €™s people are so Radical Left that **they** are working to get the Anarchists out o
 232. ught. They MUST pay a big price for what **they** have done to our Country. Don’t
 233. otal disaster they had no idea what **they** were doing. Among the worst ever! BL

Some instances of the pronoun *they* are translated into rioters (as labelled by Trump). These rioters are said to have caused trouble (example 234), to be a negative influence for the country (example 235), therefore they were all threatened because they did not respect Trump’s authority (example 236). In some specific instances, the subject pronoun *they* may relate to citizens, like in example 237.

234. do with the memory of George Floyd. **They** were just there to cause trouble. The
 235. n the Whole Wide World. No **they** are what **they** are - very bad for our Country! I
 236. s I’m your President. If **they** try **they** will be met with serious force! We did
 237. puppet Democrat Senator Joe Manchin. **They** will never forget his phony vote on th

There are also instances where the pronoun *they* is used in place of the name of a foreign country, as seen in examples 238 and 239. In these instances, the foreign nation is claimed to be doing very well against the Coronavirus.

238. attack on the Coronavirus. He feels **they** are doing very well even building hosp
 239. any and helping them in other ways. **They** are fighting hard against CoronaVirus!

However, the pronoun is more frequently occurring as standing for the media, who were said to be fighting against Trump by quoting unnamed sources (example 240), being fake (example 241), being evicted from other countries (example 242) and by failing to mention all the good actions done by Trump and his administration (example 243).

240. at are made up and knowingly wrong. **They** are doing it by quoting unnamed source
 241. us as they should? Answer: Because **they** are Fake News! Hogan Gidley will be lea
 242. s one? Are there any NAMED sources? **They** were recently thrown out of China like

243. ne the same as with the Ventilators **they** will never say we are doing a great jo

5.1.3. Information on COVID-19

This section on data presentation aims to give an account on the extent to which Trump was informative in his Twitter communication. The goals are (i) to find how COVID-19 is mentioned in Trump’s Twitter, by contrasting the frequency of use of medical denominations (like COVID) with those found via corpus analysis, to have a political intent (like China virus); (ii) to extract the frequency of lexical items related to procedures, measures and symptoms, uncovering the reasoning behind their use and their informative potential, and (iii) to extract all mentions of health workers to observe the reasoning behind their use. The analysis of lexical items related to the lemma *virus* is particularly interesting to analyse in the scope of both the cooperative principle and the conceptual metaphor.

5.1.3.1. Corpus 1

First, we observe the use of lexical items associated with the lemma *virus* on Trump’s Twitter, following the denominations used in medical discourse (as per the World Health Organization). It is possible to observe their frequency in Table 27.

Lexical items related to virus On Trump’s Twitter – According to the W.H.O.		
Phrase-Frames	Frequency	%
Coronavirus	3	n/a
COVID	0	n/a
Sars-Cov-2	0	n/a
Virus	1	n/a
Disease	0	n/a

Table 27 - Frequency of lexical items related to virus in Corpus 1, according to medical discourse, in Trump’s Twitter.

Although one does not expect the lemma *virus* to be mentioned before it struck the United States, there are some instances of the noun Coronavirus directly related to foreign affairs (Examples 244 and 245). The same happens with the lexeme *virus*, as seen in example 246.

244. s! Just received a briefing on the **Coronavirus** in China from all of our GREAT a
 245. g closely with China and others on **Coronavirus** outbreak. Only 5 people in U.S.
 246. mmunication with China concerning the **virus**. Very few cases reported in USA but

Regardless of it being redundant to observe these lexical items before the pandemic, it serves the purpose of showing how Trump created novel ways to insult enemies, through conceptual metaphors. Following Table 28, in Corpus 1, the lexeme *enemy* is aimed at specific targets, often news media (examples 247 and 248).

Lexical items related to virus On Trump's Twitter – Found Through Corpus Analysis.		
Phrase-Frames	Frequency	%
China Virus	0	n/a
Chinese Virus	0	n/a
Hidden Enemy	0	n/a
Invisible Enemy	0	n/a
Enemy	5	n/a

Table 28 - Frequency of lexical items related to virus in Corpus 1, found through corpus analysis on Trump's Twitter.

247. Amazon Washington Post. They are The **Enemy** of the People! ...The Fake News Medi
 248.The LameStream Media which is The **Enemy** of the People is working overtime wi

Concerning the symptoms tied up with COVID-19, this research extracted those reported by the World Health Organization³⁰ and crossed them with the possible findings in the tweets collected for this study. The lexical items searched for in the corpora were: *sick, fever, dry cough, fatigue, shortness of breath, loss of appetite, confusion, high temperature, exposed, infection and infected*. In Corpus 1 there was only the occurrence of *sick* and *exposed*. The first one is not connected to any disease, yet it was used as an insult by Trump, as seen in examples 247 and 248. The second lexeme does not connect with COVID-19 but with Trump's need to expose the intended weaknesses by his opponents (examples 249 and 250).

247.it to Congress as though mine! He is **sick**! All the Do Nothing Democrats are foc
 248.ORRUPT POLITICIAN and probably a very **sick** man. He has not paid the price yet fo
 249.York Post Sunday. After having been **exposed** as a fraud and corrupt can anyone i
 250.and the Witch Hunt that has now been **exposed**! There has been no President in the

According to the W.H.O., the measures to be taken during the COVID-19 crisis are: tests, isolation, quarantine, social distancing, masks, washing hands and calling the COVID-19 emergency line. As was expected, none of these are found in Corpus 1, since it is collected before the pandemic.

Concerning the procedures to be taken with infected citizens, this research filtered the corpora to find instances of: *vaccine, ventilator, antibiotics, self-medication and medicines*. As was expected, Corpus 1 does not contain any of the above-mentioned lexemes.

Finally, the study filtered the corpora to find instances related to the lexico-semantic field comprising: *doctors, nurses, physicians, world health organization, W.H.O. and hospital*. These items never occurred in Corpus 1.

³⁰ Retrieved on the 15th of May, 2021, from <https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public#:~:text=The%20most%20common%20symptoms%20of,or%20a%20skin%20rash.>

5.1.3.2. Corpus 2

Following the data in Table 29, Corpus 2 has more instances associated with the vast lexico-semantic field of the disease than in Corpus 1, because it represents a time period in which the pandemic severely hit the U.S.

Lexical items related to virus On Trump's Twitter – According to the W.H.O.		
Phrase-Frames	Frequency	%
Coronavirus	89	0,15%
COVID	19	0,03%
Sars-Cov-2	0	n/a
Virus	29	0,05%
Disease	1	n/a

Table 29 - Frequency of lexical items related to virus in Corpus 2, according to medical discourse, in Trump's Twitter.

The noun *coronavirus* gets the most mentions out of all keywords. These keywords serve the purpose of showing Trump's followers that work is being done accurately (example 251). This acknowledgment is exaggerated by Trump calling the virus a plague, yet under extinction by medical staff (hyperbole).

251. ALLY well medically on solving the **CoronaVirus** situation (Plague!). It will happ

There are some lexical occurrences in utterances in which Trump quotes unknown sources commenting on how he handled the pandemic (example 252). There are also many mentions of his coronavirus task force, which is always working (example 253) and serves the strategic purpose of showing the extent to which Trump is supposedly involved in solving the pandemic (example 254). He seems to flout the maxims of quality most of the time.

252. esident for how he has handled the **CoronaVirus** situation especially his early de

253. Great Government officials on the **CoronaVirus** Task Force who are working around

254. Ptu I will be having a White House **CoronaVirus** Task Force meeting in a short whi

COVID-19 can serve the same strategic purpose, i.e., showing involvement (example 255), yet it also serves an electoral purpose, uniting people under Trump's leadership (example 256). Furthermore, Trump placed blame on the opponents to be able to find a good reason for rallies with loads of people (example 257).

255. TORY YESTERDAY! Attending meetings on **Covid-19** in the White House. Working with

256. lity food for us during this horrible **COVID-19**. Join me in thanking our Farmers

257. ying Democrat run cities is trying to **Covid** Shame us on our big Rallies. Won't

There are some instances in which Trump created a sort of soliloquy followed by response, quoting someone and pre-emptively defending himself, as inferred in example 258. This may underpin a need to shift blame and intentionally to show citizens that he is vulnerable

and under-attack (playing the victim card). It is a clear example of negative face (face-threatening acts – FTA).

258. esident Trump was slow in reacting to **Covid 19**. Wrong I was very fast even doing

The *virus* is seen as an entity by Trump, one that is helped and manipulated by his opposition to fight against Americans (example 259). As such, it is also a discursive resource to unite citizens under Trump’s leadership (example 260).

259. ended vacation. The Democrats want the **Virus** to win? They are asking for things t
260. veloped a strong understanding of the **Virus**. We are working closely together. Mu

Having in mind the data shown in Table 30, the *enemy* takes several forms, it is abstract, undefined, both hidden and invisible, but also particularly related to China.

Lexical items related to virus On Trump’s Twitter – Found Through Corpus Analysis.		
Phrase-Frames	Frequency	%
China Virus	2	n/a
Chinese Virus	8	n/a
Hidden Enemy	2	n/a
Invisible Enemy	11	n/a
Enemy	25	0,04%

Table 30 - Frequency of lexical items related to virus in Corpus 2, found through corpus analysis on Trump’s Twitter.

Trump’s rhetoric aims at creating fear, so that he can present himself as a saviour to his citizens. Fear is created through mentions of an enemy that is hidden (example 261) and dangerously invisible (examples 262 and 623). When citizens fear for their wellbeing, they look for the leaders to guide them, and that is the strategy laid down by Trump, as seen in examples 264 and 265.

261. EVIRUS The world is at war with a **hidden enemy**. WE WILL WIN! For the people that
262. her than later the horror of the **Invisible Enemy** except for those that sadly los
263. number of their deaths from the **Invisible Enemy**. It is far higher than that and
264. pment. Together we will beat the **invisible enemy**! Such a wonderful reception yes
265. them. The People’s Voice! The **Invisible Enemy** will soon be in full retreat! N

This invisible and hidden enemy is given a form through Trump’s use of the conceptual metaphors *China virus* and *Chinese virus* (Sousa, Ivanova & Jasmins, 2020). This is evidenced in example 266.

266. ng everybody other than China for the **Virus** which has now killed hundreds of the

The virus crossed the barrier from the medical field into the realm of the foreign nation China, as seen in examples 267 and 268. It is clear that Trump’s strategy was to use the WAR metaphor, giving form to the virus, seen as an economic and political enemy, a nation, China.

267.oe. No complaints!!! The number of **ChinaVirus** cases goes up because of GREAT TES
 268.id 19 sometimes referred to as the **China Virus**. Ventilators Testing Medical Supp

Concerning the symptoms of COVID-19, Corpus 2 is also filtered in search of lexemes in the related lexico-semantic field: *sick, fever, dry cough, fatigue, shortness of breath, loss of appetite, confusion, high temperature, exposed, infection and infected*. In Corpus 2 there are nine instances of the item *sick*, one of *confusion* and another of *infected*. The lexeme *sick* is used once as an insult (example 269), yet it also connects with the pandemic. That occurs through the mentions of sick leave (example 270) and of people feeling sick (example 271). The impact of this multitude of encoded meanings may lead the hearer to confusion and misinterpretation.

269.laming RUSSIA RUSSIA RUSSIA. They are **sick** losers with VERY bad ratings! P.S. Ca
 270.n for free CoronaVirus tests and paid **sick** leave for our impacted American worke
 271.I NEVER said people that are feeling sick should go to work. This is just more

The keyword *confusion* does not relate to a symptom, but to the goals of news media in the pandemic scenario (example 272) and the lexeme *infected* follows the same goal, as seen in example 273.

272.he purpose of creating conflict and **confusion** some in the Fake News Media are sa
 273.ike! Diagnosis positive: @CNN is **infected** with Trump Derangement Syndrome. I'm

Likewise, Corpus 2 is filtered for the scrutiny of instances associated with measures to be taken during the COVID-19 crisis (as recommended by W.H.O.), i.e., *tests, isolation, quarantine, social distancing, masks, washing hands and calling the COVID-19 hotline*. Their use on Corpus 2 is scarce, as seen in Table 31, and these keywords do not seem to play an informative role, as might be expected in Trump's Twitter rhetoric (flouting the maxim of relevance and mode).

Measures taken during the Covid-19 Crisis – Searched in Trump's Twitter		
Keyword	Frequency	%
Test/s	11	0,01%
Isolation	0	n/a
Quarantine	2	n/a
Social Distancing	4	n/a
Mask/s	9	n/a
Wash hands ³¹	0	n/a
COVID-19 hotline	0	n/a

Table 31 - Frequency of lexical items related to measures, searched in Trump's Twitter.

Following Table 31, the concrete noun *test* (plural and singular forms) was neither used informatively nor to convince citizens to get tested, it functioned rather as a bragging tool, a

³¹ All variations of these keywords are also searched for, like washing your hands or please wash your hands.

resource to demonstrate the superiority of the United States against other countries (examples 274 and 275).

274.and available. Just passed 5 Million **Tests** far more than any other country in t
275.before if necessary! We pass 15000000 **Tests** Today by far the most in the World.

The second keyword underused by Trump was *quarantine*. It was not used to offer advice (as in self-quarantine), yet it was covered in utterances that inform on the decisions and courses of action likely to be taken by the government, which can change often, as shown in examples 276 and 277.

276.the....Federal Government. A **quarantine** will not be necessary. Full detail
277. I am giving consideration to a **QUARANTINE** of developing hot spots New

Neither *social distancing* nor *physical distancing* were used a lot, as was expected. But the former occurred when Trump commented on the state of affairs, often assuring that everything was already being done (example 278). Otherwise, it occurred through seemingly random capitalizations and exclamation marks (example 279), clearly flouting the maxim of manner and quantity.

278.n people are doing a great job. **Social Distancing** etc. Keep going! On National F
279.great job. Full report latter! **SOCIAL DISTANCING!** News Conference at White Hous

Concerning the keyword *mask/masks*, these are not encoded by Trump as a medical resource, they are given an economic value, powering the American economy thereby playing an hegemonic role towards other countries (examples 280). Nonetheless there was one utterance with an instance where Trump advised the use of masks (example 281), once again, he ended up speaking more commonly about his own use of (or failure to use) masks (example 282). Apart from the strategies already mentioned, underestimating serious issues for personal rhetorical gain (euphemisms) features Trump's pragmatolinguistic and discursive style.

280.The World market for **face masks** and ventilators is Crazy. We are hel
281.in the World. Also gear up with **Face Masks!** Fake News!
282.nspectd a Ventilator plant without a **mask**. Not their fault and I did put on a

Concerning procedures taken with infected citizens, Corpus 2 is also filtered to find instances of: *vaccine*, *ventilator*, *antibiotics*, *self-medication* and *medicines*. Table 32 shows the only keywords which occur in this corpus.

Procedures Taken with Infected Citizens – Searched in Trump’s Twitter		
Keyword	Frequency	%
Vaccine	7	n/a
Ventilator/s	41	~0,06% ³²
Medicine	1	n/a

Table 32 – Frequency of lexical items related to procedures, searched in Trump’s Twitter.

In Corpus 2, there were some instances of vaccine(s) and medicines and several instances of ventilator(s). Most often these keywords are not used with the intention of being informative or with the purpose of following the recommendations strongly advised by doctors, but are seen as a way to show what the United States is doing more and better than other nations. Following the same strategy laid down beforehand for the lexeme tests, the noun *vaccine* is used to create promises and a connection with Americans (examples 283 and 284).

283.to prevent detect treat and create a **vaccine** against CoronaVirus to save lives i
 284.g. America is getting its life back! **Vaccine** work is looking VERY promising befo

Echoing the analysis of the keyword *mask(s)*, the lexeme *ventilators* became an economic resource, a tool for trading – as seen above, in example 280, but also in examples 285, 286 and 287. The keyword does also find some use in bragging, like *tests*, having in mind that Trump is doing much better than other countries (example 288). Concerning the lexeme *medicine*, Trump commented on the field and not on types of remedies – as seen in example 289.

285.t but it is not easy. Just got 400 **Ventilators** for @NYCMayor Bill de Blasio. Wor
 286.ds Will be immediately sending 100 **Ventilators** to Colorado at the request of Sen
 287.that the United States will donate **ventilators** to our friends in India. We stand
 288.We have done a great job on **Ventilators** Testing and everything else. Were
 289.est game changers in the history of **medicine**. The FDA has moved mountains - Than

Observing now if and how health staff are mentioned, this research filtered Corpus 2 to find instances associated with: *doctors, nurses, physicians, world health organization (or W.H.O.) and hospital*. The set of data is presented in Table 33.

Medical Workers – Searched in Trump’s Twitter		
Keyword	Frequency	%
Doctor/s	10	0,01% ³³
Nurses	6	n/a
Physician/s	3	n/a
World Health Organization	2	n/a
W.H.O.	4	n/a
Hospital/s	24	0,02% ³⁴

Table 33 - Instances of lexical items related to medical workers, searched in Trump’s Twitter

³² This value is only for the plural form.

³³ Value for the plural.

³⁴ Value for the plural.

In Corpus 2, *doctors* and *nurses* are referred as if they did not belong to the medical field and turned, via a conceptual metaphor, into soldiers in the frontlines of a battle (Sousa, Ivanova & Jasmins, 2020). This metaphor is seen in example 290. Also, doctors are praised, not because of the valuable work they are doing, but because these medical workers, as well as nurses, place the United States over other countries (as seen in examples 291 and 292). There is also a single instance where Trump expresses gratitude towards nurses and physicians, that is implicit in example 293.

290.for their tireless work. **Doctors** and **nurses** are at the front lines of this war a
291.alth is home to some of the greatest **doctors** scientists and researchers in the w
292.e world. We have the best scientists **doctors nurses** and health care professional
293.EVAIL! Today I spoke with American **physicians** and **nurses** to thank them for their

When it comes to the W.H.O., Trump showed some disregard towards the organization, because he often claimed unfair treatment (example 294), seemingly rather favourable towards China³⁵. He further claimed that W.H.O.’s analysis of the pandemic was inaccurate (example 295). As a practical leader, he was building an undue negative face of the country (FTA).

294.ny fraction of \$’s to The **World Health Organization** The United Nations and wor
295.ransmitted between humans? Why did the **W.H.O.** make several claims about the Coro

Concerning the last keyword, *hospital*, it was mentioned in an informative manner, as seen in examples 296 and 297, yet it was also employed as a way to show the great work undertaken by Trump’s administration, as perceived in example 298.

296.Bill de Blasio. Work beginning on 4 **hospitals** in New York! Millions of different
297.ve amounts of medical supplies even **hospitals** and medical centers are being deli
298.ight week span. Great job! The four **hospitals** that we (FEMA) are building in NYC

5.1.4. Vague Expressions

Parvaresh (2017)³⁶ divided expressions into several categories: vague estimators, vague possibility indicators, vague extenders, vague boosters, vague de-intensifiers, vague nouns and vague subjectivisers. With these, the author collected vague expressions used by Trump during his 2016 campaign, these expressions are now under scrutiny, in this study, to find their frequency of use and pragmatic meaning.

³⁵“Why is it that China for decades and with a population much bigger than ours is paying a tiny fraction” – Full tweets found through the Tweets’ IDs: 261793132020224005 and 1261793147069366279

³⁶ Vague language is a common feature of both written and oral language (Cutting, 2007), implting ambiguity in communication, and in it lies a new way to inquire on language use (Fernández & Yuldashev, 2011). Some of the language items are identified in Channell (1983). *Vague language: some vague expressions in English* (Doctoral dissertation, University of York). Observing vagueness from the lens of discourse (Parvaresh, 2017), it becomes apparent that people use vague words and phrases with general meanings on purpose to be non-specific (Carter & McCarthy, 2006). Vague expressions can be negotiable but depend on “assumptions of shared knowledge between the speaker and the hearer” (Parvaresh, 2017:170).

5.1.4.1. Corpus 1

Observing Table 19, it is clear that the vague expression *very* was the most used by Trump in his Twitter communication. It is closely followed by the lexeme *so*.

Vague Expressions in Corpus 1		
Keywords	Frequency	%
Very	248	0,37%
So	232	0,35%
More	150	0,22%
Would	143	0,21%
Many	130	0,19%
Much	99	0,15%
Really	56	0,08%
Some	45	0,07%
Thing	39	0,06%
Millions	27	0,04%
Things	26	0,04%
Something	20	0,03%
I think	16	0,02%
A lot of	15	0,02%

Table 34 - Frequency of vague expressions in Corpus 1. Organized from the most frequent to the least

Firstly, observing the pragmatic meaning behind the intensifier *very* in Corpus 1 (cf. Table 35), a vague booster used to convey conviction (Parvaresh, 2017). It is used to show what Trump understood vaguely as lies (example 299). It was further used to signify that Trump's enemies were going to pay some sort of price (example 300). Following Trump's perspective of the world around him, the adverb seemed to be used to define the line between good (examples 301 and 302) and bad (303 and 304).

Cluster of Vague expressions in Corpus 1		
Keywords	Frequency	%
A very *	26	0,04%
So many	20	0,03%
And * more	11	0,02%
Would be	39	0,06%
And many *	12	0,02%
Much more	21	0,03%
Really good	8	0,01%
Some of	8	0,01%
Whole thing	7	0,01%
Millions of *	17	0,03%
Great things	5	n/a
Something very	3	n/a
I think *	11	0,02%
A lot of	15	0,02%

Table 35 - Cluster of vague expressions extracted from Corpus 1.

299.ly to that story knowing that it was a **very** big lie. Now they say that they had
300.any of our facilities. They will pay a **very** BIG PRICE! This is not a Warning it
301.Impeaching the President for having a **very** good conversation with the Ukrainian
302.ies. NYPD Commissioner is resigning! A **very** good start! Please all work hard to
303.the Media! The LameStream Media had a **very** bad week. They pushed numerous phony
304.een enriching uranium. THAT WOULD BE A **VERY** BAD STEP! A great new book just out

The former president was resourceful in his way of accounting for facts, often making use of abstractions and ambiguity. For instance, the vague quantifier *so many* can be associated to people (example 305), to issues (example 306) or to countries (example 307). The same occurs with the lexemes *more* and *much*, which are often used together or with the lexeme *many*, as seen in examples 308 and 309 – these are further intensified by the lexeme *so*. Overall, they may be taken as fixed phrases used as fillings devoid of meaning rather than the one of vindicating Trump’s populist agenda and playing the saviour.

305.s..statement. Strange that with **so many** other people hearing or knowing of
306.g Apple all of the time on TRADE and **so many** other issues and yet they refuse to
307.Trade also. Will change! Germany and **so many** other countries have negative inter
308.ave Schiff the Bidens Pelosi and **many more** testify and will reveal for the first
309.ls help for working families and **much more**. Over the last 3 years unemployment f

In the case of the modal *would*, it occurs often next to the pronoun *it*, creating assumptions of what and how situations should play out (examples 310 and 311).

310.jail for treason (and more) and it **would** be considered the CRIME OF THE CENTURY
311.emocrats could end Loopholes and it **would** be a whole lot easier and faster. But

The adverb *really* is seemingly used to inculcate the idea that Trump’s actions were really good, as seen in examples 312 and 313.

312.rning out to be good for me - some **really** good! He’s got all meetings locked d
313.is good will on both sides and a **really** good chance for success. The U.S. has

Going back to vague quantifiers, the indefinite *some* is employed when the factual number is not known, concerning economy (example 314), the people (example 315) and even the quality of doctors (example 316), in Trump’s tweets.

314.t Sleepy Joe Biden. Will fail again! **Some** of the best Economic Numbers our Count
315.this morning by @foxandfriends with **some** of the fantastic people who attended t
316.Reed Medical Center. Those are truly **some** of the best doctors anywhere in the wo

Hence, and by contrast, the lexeme *thing* was used to group all of the opponents’ actions, particularly their ideas, which caused *issues* (example 317) and were considered *jokes* (example 318). This contrasts heavily with the plural *things* which is often seen next to the adjective great (collocate) and gains a positive polarity (example 319). In the same fashion, as the lexical item *thing* (singular), the lexeme *millions* modifies dollars (example 320), people (example 321) and even quantifies lives (example 322). This use of vague quantifiers

(hyperbole) shows a disregard towards factual information, either on purpose to protect face or through ignorance.

317.iff and the Dems have created this whole **thing** they reverse engineer it. They
318.Dems) don't have anything. This whole **thing** is a joke and it's time to get
319.ttling a President who is getting great **things** done for our Country at a record
320.ped off at least two countries for **millions** of dollars calling for my impeachmen
321.begin on Phase Two! To those many **millions** of people in Iraq who want freedom a
322.s and many thousands of lives (and **millions** of lives when you count the other si

The indefinite compound *something* defined as an unspecified thing or a thing up to some extent (according to the Oxford Dictionary, 1979), is used by Trump to separate what is good from what is bad (examples 323 and 324).

323.statement I thought I was doing **something** very good for our Country by using Tr
324.ident to make it look like I did **something** very wrong. He then boldly read those

Parvaresh (2017) identified the phrase *I think* as a vague subjectiviser, and found it often in Trump's campaign. In this piece of research, it also shows some evidence, mainly with the purpose of giving opinions, even though with low commitment (Parvaresh, 2017). Trump belittled Chinese citizens (example 325) and the opponents (example 326). He also makes assumptions regarding the American citizens (example 327).

325.ed at is how strong the consumer is. **I think** the Chinese need it (a deal) more t
326.s of any kind. That says it ALL! **I think** that Crooked Hillary Clinton should
327.but because they hate the president. **I think** the American people know that this

Finally, concerning the least frequently used vague expressions, i.e., *a lot of*, it correlates with news (example 328), people (example 329), money (example 330) and even abstract values such as winning (example 331), broadening the semantic field.

328.w and that's all that is important! **A lot of** Fake News is being reported that
329.rated all over the World. They showed **a lot of** people how strong the Republican
330.toried history. Not only is it losing **a lot of** money but it is a journalistic di
331.. Great reaction under pressure Tate! **A lot of** winning in Kentucky. Check out th

5.1.4.2. Corpus 2

Switching over to Corpus 2 and for consistent procedures to be followed, it is filtered to extract the same or other occurring vague expressions as in Corpus 1. The following Table displays the organization of the data retrieved from the corpus.

Vague Expressions in Corpus 2		
Keywords	Frequency	%
Very	225	0,37%
So	175	0,29%
More	151	0,25%
Would	113	0,19%
Many	112	0,19%
Much	75	0,12%
Really	50	0,08%
Things	44	0,07%
Some	36	0,06%
Thing	23	0,04%
Millions	19	0,03%
Something	13	0,02%
A lot of	11	0,02%
I think	9	0,01%

Table 36 - Frequency of vague expressions in Corpus 2. Organized from the most frequent to the least

In Corpus 2 (cf. Table 37), in which most phrase-frames are either the same or similar to those occurring in Corpus 1, the adverb *very* is used to cover what is good and what is bad (as seen in examples 332 and 333). It can also be a measure for defining and intensifying what is big and what is small (examples 334 and 335).

Phrase-frames of Vague expressions in Corpus 2		
Keywords	Frequency	%
A very *	67	0,11%
So called	16	0,03%
More than *	40	0,07%
Would be	28	0,05%
And many *	25	0,04%
Much more	14	0,02%
A really *	19	0,03%
Great things	8	0,01%
Some of	6	n/a
The * thing	6	n/a
Millions of *	24	0,04%
Something that	3	n/a
A lot of	11	0,02%
I think	9	0,01%

Table 37 - Phrase-Frames of vague expressions extracted from Corpus 2.

332.e Virus very seriously and have done a **very** good job from the beginning including
 333.d Iran would have a field day. Sends a **very** bad signal. The Democrats are only d
 334.that. The only person that can claim a **very** big victory in Iowa last night is
 335.s on the Coronavirus situation. Only a **very** small number in U.S. and China num

The adverb *so* occurs in utterances that undermine the value of anyone other than Trump, like protesters (example 336) and reporters (example 337).

336.HOUSE??? The professionally managed **so**-called protesters at the White Hous
 337.e for Ronny on Tuesday March 3rd! A **so**-called reporter named @JohnJHarwood who b

The vague quantifier *more* occurs when Trump placed himself and his country above every other nation (example 338 and 339).

338.other country in the world. In fact **more** than all other major countries combined
339.the U.S. because we are testing far **more** than any other country and ever expandi

Delving into the realm of possibility, Trump used the modal *would* to assume the future of situations (remote possibility and threat, representing a face-threatening act), often to show how bad these could be (example 340) or to show how the opposition parties foiled his chances at success (example 341).

340.e must be very careful. Crazy Nancy **would** be a total disaster and the USA will n
341.Jobs Military Vets 2A and more I **would** be at 70%. Oh well what can you do? Ht

The determiner *many* connects to an undetermined “other”, either an expense (example 342) or someone who sides with Trump (example 343). Concerning this use of abstract amounts, the word *much* works similarly to support arguments made by Trump with imprecise information, for instance, regarding the COVID-19 tests (example 344) and corruption (example 345).

342.government for money to carry this and **many** other very expensive to carry prope
343.hip style or much else about him and **many** others agree. Glad he is gone! I fe
344.h greater (25 million tests) and so **much** more advanced that it makes us look lik
345.. It was corrupt in 2016. Now it is **much** more corrupt and what you are seeing is

Although predominantly positive, but emphatically tuned, in this piece of research, the adverb *really* does also share the bipolarity common in Trump’s rhetoric. It is either used to qualify people positively, like in examples 346 and 347, or to insult the actions of the opposition, as seen in examples 348 and 349.

346.ent....My co-chair in Utah and a **really** great guy. Sean has my Complete and
347. News knows this. Thanks Katie! A **really** great woman and what a job she is doing
348.ared tomorrow they would say we did a **really** poor and even incompetent job. Not
349.referred to as Pocahontas is having a **really** bad night. I think she is sending s

Trump stated that he did a lot in many different sectors, yet he did not specify what and how. He mentioned his actions as doing great *things*, particularly concerning the pandemic (examples 350 and 351).

350.hospitals and beds and soon the great **things** we are doing on testing. People a
351.r and more efficient in the area! Great **things** coming to Arkansas! \$40M to be aw

By scrutinizing the meaning behind the lexeme *some*, as in the analyses done beforehand for Corpus 1, it is unspecific in what it refers to. Sometimes this was evidenced in Trump’s mentions of regulations (example 352) and other times with his mention of countries that were being helped (example 353).

352.est in the World....I have seen **some** of the regulations being circulated in
353.dealing with the CoronaVirus problem **some** of which we are helping! Just had a gr

Observing the lexeme *thing*, defined as an unnamed object or item in the Oxford Paperback Dictionary (1979), it undermined the actions of the opposition, as evidenced in examples 354 and 355.

354.e. Glad he is gone! Probably the only **thing** Barack Obama & I have in common
355. analysis for yourself. This is the same **thing** they and others did when we defeated

The vague quantifier *millions* is once more related to unspecific amounts. It modified people (example 356) and money (example 357) as well as masks (example 358).

356. ences are vital. They are reaching **millions** of people that are not being told th
357. rs have everybody arrive and... ..**millions** of dollars and jobs for the State. B
358. use it because no one has said NO! **Millions** of masks coming as back up to States

Parvaresh (2017) classifies the word *something* as a vague extender which is crucial in communication. For Trump, the lexeme *something* modified actions, as seen in example 359.

359. December 31. Then you are doing **something** that is really meaningful. Only that

Regarding citizens, the phrase *a lot of* is used to quantify, in abstract terms, both people and communities (examples 360 and 361), but also money (example 362) and respect (example 363).

360. so doing. Most importantly we helped **a lot of** great people! Joe Biden's handl
361. HUGE for safety info and broadband in **a lot of** communities that need it! .@SCDOT
362. e are betting big against it and make **a lot of** money if it goes down. Then they
363. His incredible wife Karen who I have **a lot of** respect for once pulled me aside

Finally, the phrase *I think* is used to show low commitment when making comments, which could always be explained, if needed, to protect face – this is possibly illustrated in examples 364 and 365. As for other sections of this research, it is evidenced that Trump's strategies were often the same pre-and post-pandemic ones, what changed was associated with topics addressed.

364. hontas is having a really bad night. **I think** she is sending signals that she wan
365. ELING! I am a big fan of Drew Brees. **I think** he's truly one of the greatest qu

5.2. Discussion

5.2.1. Contrasting Data

Having analysed the data in both corpora, there were some similarities as well as some clear shifts in Trump's lexical choices. More particularly, the nouns *president*, *Democrats*, *nothing*, *impeachment*, *people*, *Trump*, *news*, *Republican*, *country*, *Schiff*, *house*, *American*, *time*, *years* and *party* (frequency range: – 377-105) from Corpus 1, and: *people*, *news*, *total*, *job*, *country*, *endorsement*, *president*, *states*, *Joe*, *military*, *state*, *nothing*, *democrats* and *coronavirus* (frequency range 232-89) from Corpus 2. The first clear difference is found in the

conditions set for the extraction of nouns when it comes to their frequency, which, as previously explained in this piece of research, is expanded to include the keyword *coronavirus*. This noun is highly relevant to the theme of this research study because of the time-period under analysis.

There was a clear shift in Trump`s addressee, from Schiff to Joe. Also, there was a shift in the topic that was criticised the most by Trump, the impeachment hoax, which was left behind, giving place to Trump`s plans for the endorsement of his party. Lastly, in Corpus 1 Trump made several references to time and space, while in Corpus 2 these were not found among the most frequent nouns.

As shown in the results section, in order to better comprehend the co-text of keywords, their clusters were extracted so that pragmalinguistic and discursive choices could be analysed in the light of the literature in the field mentioned beforehand. Corpus 1 presented: the **president** of; do **nothing democrats**; the **impeachment** hoax; the **American people**; that president **Trump**; the fake **news**; the **Republican party**; of our **country**; shift Adam **Schiff**; the White **House**; the same **time**; for many **years**. Consequently, Corpus 2 demonstrated: the **people** of; the fake **news**; complete and **total**; a great **job**; of our **country**; and total **endorsement**; **president** of the; the United **States**; sleepy **Joe** Biden; loves our **military**; the great **state**; do **nothing Democrats**; **coronavirus** task force.

It becomes clear that the nouns which are repeated in both corpora were assigned different meanings in their co-text. For instance, the noun *people*, which at first had a clear referent, Americans, is then given a more specific referent, the citizens of the different states. Otherwise, the people who Trump referred by name were often insulted, as seen in “shift Adam Schiff” and “sleepy Joe Biden” (face-threatening act). The same occurred with identifiable groups, like the Democrats which are said to “do nothing”.

The same procedures were devised in the analysis of for the adverbs. These are the same in both Corpus 1 and Corpus 2, due to their relative frequencies. In Corpus 1, ranked from the most frequent to the least frequent one finds: *not*, *very*, *just*, *now*, *never*, *up* and *more* – ranging in frequency from 256 to 150. In corpus 2, also ordered from the most frequent to the least frequent one finds: *very*, *not*, *just*, *now*, *more*, *up* and *never* – ranging in frequency from 225 to 105. At first glance, one can observe that both *not* and *very* are the most frequent adverbs, whereas *up* and *more* are less frequent. When observing the keywords/lemmas beyond the co-text, one may assume that they are used relatively for the same purpose and, as such, there are

no major differences for contrasting. For that reason, their clusters are extracted, to give a better understanding of the meaning behind lexemes.

So, at first, in Corpus 1 one finds: is **not** *; a **very** *: **just** * the; Democrats are **now**; will **never** *; made **up** *; and * **more**. While from Corpus 2 are extracted: a **very** *; will **not** be; **just** spoke to; we * **now**; **more** than *; **up** * great; will **never** *. The clearest difference found is that the co-text of the adverb *now*, which at first was used to modify the actions of the Democrats; yet it shifted afterwards to the actions associated with the collective “*we*”. This shows a shift in the immediate focus from the OTHER to US.

Expressions of immediacy are found throughout Corpus 2, observable with the lexemes *now* and *just*. The latter showed that Trump wrote amidst affairs or right after these occurred, as evidenced with the people he “just spoke to”.

Now focusing on adjectives, these follow a similar pattern to that of adverbs. That is so, because the same lexical units are also found in both corpora. However, the difference here was that the condition for extraction was not the frequency, since adjectives ranged from very high frequencies to very low ones. Thus, a decision was made to extract the five most frequent adjectives, allowing for a broad view into the way they are used by Trump. In Corpus 1 one finds: *great*, *big*, *new*, *good* and *wrong* – ranging in frequency from 440 to 84. In Corpus 2 one finds: *great*, *big*, *new*, *strong* and *good* – ranging in frequency from 515 to 96. The one difference found in plain keywords, is that in Corpus 1 one finds the adjective *wrong*, while in Corpus 2 one finds the adjective *strong*. It is worth mentioning that the frequency of adjectives is much lower in Corpus 2 when contrasted with Corpus 1.

Once more the analysis needs the co-text provided by clusters to better infer the meaning behind adjectives. Therefore, clusters/phrase-frames are extracted as follows: from Corpus 1: a **great** *; a **big** *; **New York** *³⁷; a very **good**; did nothing **wrong**; from Corpus 2: a **great***; a **big** *; **New York** *; **strong** on; a very **good**. From this set of data, it seems that the lexeme *new* was used often either to mention or to comment on the actions of the New York Times newspaper. It also becomes clear that Trump often remarked that his actions were very good, and he often said he had done nothing wrong. As mentioned in the previous section of

³⁷ Cf. note 25

this chapter, it was expected to find these adjectives in Trump's rhetoric, due to their dissemination in the news media (press).

Switching the focus to subject pronouns, this research collected the five most frequent, out of which one cluster was extracted for each pronoun. This gave a general grasp of the context and established the basic differences between the use of pronouns in the Twitter communication by Trump. Then, for further analysis, several clusters/phrase-frames were extracted for each individual pronoun: *I, they, you, we, he* – ranging from 550 occurrences to 311 from Corpus 1 – and: *I, you, they, we, he* – ranging from 528 instances to 337 from Corpus 2.

Focusing only on the first and main cluster of each pronoun, Corpus 1 demonstrated: **I will ***; **they are ***; thank **you ***; **we are ***; **he is ***, while Corpus 2: **I will ***; thank **you ***; **they are ***; **we are ***; **he is ***. From this perspective, the same clusters are identified and that does not allow for a contrastive analysis of the many possible differences between time-periods. Thus, several clusters are collected from each pronoun, eventually constituting grounds for comparison between Corpus 1 and Corpus 2.

Starting first by the scrutiny of the first-person singular, the clusters extracted out of Corpus 1 are: **I will ***, **That I ***; **I have ***; **I * nothing**; **I don't ***, from Corpus 2: **I will***; **I * be**; **I am***; **that I ***; **I was ***. Considering the data scrutinised, it appears that the pronoun is self-referential in both corpora. In Corpus 1 it has a larger use of negative language (negative semantic prosody), following the instances of *nothing* and *don't*. Corpus 2 however, seemed more focused on time, particularly the past and the present of Trump himself, with instances of "*I am*" and "*I was*".

Considering the first-person plural, the clusters extracted out of Corpus 1 are: **we are***; **we will ***; **we have ***; and **we ***; **that we*.**; and: **we are ***; **we will***; **we have ***; **we * be**; together **we *** from corpus 2. Not only are the data taken from both corpora similar, but it is also apparent how similar these phrase-frames are to those found before for the first-person singular. This could mean that the pronoun reference *we* is an extension of the first-person singular *I*. It is also relevant to note that one of the collocates is the lexeme *together* and that it is extracted from a period under the threat of a virus, signalling a need for citizens to get together and fight.

Observing the use of the second-person *you*, the clusters extracted out of Corpus 1 are the following: thank **you ***; see **you ***; **you to ***; if **you ***; **you * the**. And the clusters extracted

from Corpus 2 are: thank **you** *, **you** to *; **you** * a; **you** have *; **you** are *. At first glance there are not many differences from Corpus 1 and Corpus 2, albeit we find the conditional being used in Corpus 1, “*if you*”, and the possessive in Corpus 2, “*you have*”.

The third-person singular is extracted in the same fashion as the previous pronouns, at first from Corpus 1 are extracted: **he** is *; **he** will *; **he** has *; **he** loves our; that **he** *. And from Corpus 2 the ones extracted are the following ones: **he** is *; **he** will *; **he** * a; **he** * our; and **he** *. At a first glance it is noticeable that a single one of the cluster is not a phrase-frame, particularly the one which mentions someone’s love for something.

Lastly, focusing on the third-person plural *they*, from Corpus 1 are retrieved: **they** are *: **they** don’t *; **they** have *; **they** * the; and **they** *. From Corpus 2 are extracted: **they** are *; **they** were *, **they** * doing; what **they** *; **they** will *. Here this piece of data gives a window into different co-texts. In both corpora the focus is on the actions of the OTHER, on what they are³⁸ doing, were doing and will do. Finding similarities between corpora, concerning parts-of-speech, reveals a lot about Trump’s rhetoric and his pragmatolinguistic choices, showing how he followed a very repetitive pattern in his Twitter communication.

Switching over to the section where information on COVID-19 is examined, a contrast is not possible, since most of the keywords under analysis can only be found in Corpus 2. That is expected as Corpus 2 covers a time-period affected by the pandemic, while Corpus 1 does not. Still, as seen in the previous section of this chapter, some keywords that were expectedly within the lexico-semantic field of medical issues are taken out of this field, through conceptual metaphors, to insult, as exemplified in several speech acts related to the lexemes *virus* and *exposed* (and briefly mentioned in the analysis of the date).

Finally, one places the data concerning vague expressions under scrutiny. From Corpus 1 the extracted expressions are the following: *very*; *so*; *more*; *would*; *many*; *much*; *really*; *some*; *thing*; *millions*; *things*; *something*; *I think*; *a lot of* – ranging in frequency from 248 to 15. From Corpus 2 the same expressions were extracted but, due to their frequency, they come in a somewhat different order, as follows: *very*; *so*; *more*; *would*; *many*; *much*; *really*; *things*; *some*; *thing*; *millions*; *something*; *a lot of*; *I think* – ranging in frequency from 225 to 9. Concerning raw data, there is not much to contrast here without the broadened co-text of concordance lines, since even with the extraction of clusters, this set of data is very similar and,

³⁸ At the time of Trump’s writing.

in some ways, identic. Although there are two different time-periods, the linguist choices by Trump remained the same, underpinned by a colloquial undertone dictated by the medium (Twitter) but replicating his communicative style in other media.

5.2.2. Populist Rhetoric

As seen in the literature review (*cf.* Chapter 3), Trump was often considered populist by scholars, and that is also evidenced in this research. At first, we find a rhetoric that focuses heavily on the vilification of the OTHER (Lacatus, 2019), whose mistakes made in the past are never forgiven and were brought up by Trump, as evidenced in Corpus 1 and Corpus 2. These supposed mistakes allowed the country to reach what Trump called a “bad state”, in the process losing all of its important values (Hidalgo-Tenorio & Benítez-Castro, 2021).

The country itself is evidenced in both corpora to be a place of war, and in this battlefield, Trump fought those who threatened the values of the United States, thus approaching the topic of politics through the WAR metaphor. This use of the conceptual metaphor of WAR seemed to have a high engagement with audiences (Anderson, 2017) and helped to manipulate citizens into following Trump into the battlefield.

Donald Trump presented himself as a saviour (Hidalgo-Tenorio & Benítez-Castro, 2021), equal to citizens and fighting side by side with them against all (imagined) threats. These threats were often said to occur because of the Democrats. This common strategy in populist discourse (Oliver and Rahn, 2016; Savoy, 2017; Appel, 2018; Lacatus, 2019; Hidalgo-Tenorio & Benitez Castro, 2021), saw the Democrats vilified as figures capable of great harm to the nation, which only Trump could solve, since he was able to nullify all their actions, evidenced in the way he insisted on calling them the “do nothing Democrats” (FTA).

He often stated that the nation had many issues to be solved, which threatened their power, yet when asked by the media to better specify what he meant, he could not do it. This led Trump placing upon himself both the role of exposing which media was fake and of exposing those who helped the media, for instance Joe Biden. This is a significant instance of blame-shifting, where Trump assumed and stated that he was being attacked by his opponents, who were perceived to be constantly trying to destroy his image and block his progress.

Trump presumably felt like he was the one to report on the wrong and bad, to warn citizens and unite them, creating an army capable of fighting against the enemies, the opposition. This enemy, “the other”, was very often threatened by Trump over its big lies,

which were said to cause a very bad time for all American citizens. This sometimes specific and other times vague “other” was accused of scheming “something” and making “stuff up” to ruin Trump and destroy the lives of Americans.

However, rather interesting is how the OTHER was seen as an evil capable of destroying the nation, yet, at the same time, it could be easily stopped if Trump intended to. Trump made sure his audiences knew about this, and that they would remember the past mistakes of the opposition, through which, he stated, audiences could clearly see he was a better and true leader. They could further evidence this by reportedly just reading about it or if his enemies would just admit to this truth.

Placing Corpus 2 under scrutiny, a time-period which was under the shadow of COVID-19, the strategy remained the same. The virus is vilified and said to be the biggest threat to Americans, even sometimes called a plague, but, again, it is easily defeated by Trump if he wanted to and people should have followed him to survive. Trump considered that his decision making placed the United States above all foreign nations in the fight against the coronavirus, and made sure to state that often.

This celebration of his own achievement (Lacatus, 2019) is another clear marker of populist discourse, and it was found in both corpora under analysis. At first, the simple act of always mentioning the wrongdoings of other people placed Trump on a pedestal, on which his actions always looked better and overwhelmingly positive or, as he stated, very good, very large and very important. This intrinsic value was transferred to those who surround Trump, which were said to be great and valuable, although he never gave them differential treatment and they were just a collective with shared values. Among the many values that Trump endorsed in his party, the most prevalent ones were their love for the military, the vets, the border and lower taxes. Trump and his party were always doing a “great”/“good” job, yet when the news media said otherwise, they were accused of creating fake narratives and of siding with the opposition (face threatening acts). When it came to the way Trump managed the pandemic, any bad comment was said to be a strategy to confuse the nation.

This celebration of success is further overreacted when Trump said he was doing better than every single other country against the pandemic (that he calls a very bad gift from China), boasting (flouting the maxim of quality) something that is not evidenced. He seemed to minimize every mistake done during this period by repeating often that he was producing and

giving a lot of ventilators to those who needed them and also explained that the United States only had a high number of infected because he was doing more tests than every other country. Trump went as far as insinuating that there were no mistakes in his actions, and that these could only get better and better with time. His success is reportedly supported by many or millions of unknown citizens who are quoted saying he was doing well.

Political power gave Trump the power to decide between what was good and what was bad, something he manipulated often to state how everything should or not be done. He aimed for the betterment of political order (Lacatus, 2019) by criticizing and threatening those who opposed his view and did not follow his command. All this power gave him the ability to act as a supreme leader, who took decisions authoritatively and punished everyone who did not submit to his rule.

Trump often used Twitter as an outburst for his emotions and feelings, and his frequent self-references were filled with promises for the future. Trump stated that he was being mistreated by the opposition, by the media and by the World Health Organization, repeating often that he did nothing to deserve such treatment and that it was also an attack on American citizens. Although it is evidenced that Trump's rhetoric was emotional, direct, uncivil and simple (Lacatus, 2019; Appel, 2018; Oliver & Rahn, 2016; Hidalgo-Tenorio & Benítez Castro, 2021; Savoy, 2017; among others), his use of vague expressions showed that he did not commit to his own opinions and always had a way to dismiss commitment.

5.2.3. COVID-19 as an Opportunity

Through his Twitter communication Trump would sometimes minimize the danger of COVID-19 and other times maximize it, leaving citizens confused and in distress. According to Homolar & Scholz (2019), Trump's success came mostly out of his use of crisis rhetoric, where he pretended the country was at risk and manipulated citizens into following him if they wanted to be protected and get their rights back. This forced citizens into fighting against the many enemies of the United States.

Trump further strengthened his position as a leader by placing blame on past administrations, and stating that the issues that occurred during the pandemic were only possible because those who came before failed. Trump stated that COVID-19 was a plague, maximizing its danger and stated that Americans could only defeat it if they followed him.

COVID-19 was an electoral weapon, helping to unify citizens under Trump's leadership. The former president showed himself always involved in solving the pandemic with the coronavirus task force and debated himself online to justify his decision to organize rallies. Moreover, Trump often promised a vaccine for all Americans and constantly bragged about how well the United States was doing in comparison with other countries. This was so because of the many ventilators they were producing and giving to others in need and because of the many tests they were doing, which were said to be much more than all other countries.

The virus was made to be an entity, which was helped by the opposition to further attack the citizens of the United States and completely destroy the country. In simple terms, Trump's strategy is summarised as creating fear and then solving it. He first created fear among citizens by stating that the virus was both hidden and invisible, these citizens were then forced to look up to their leader if they wanted to survive. After gathering the attention of all citizens, intensifying their fear and maximizing their distress, Trump gives a body to the virus, connecting it with China. Trump called COVID-19 the Chinese virus or the China virus, turning it into the enemy of the Americans and into an economic and political enemy (Sousa, Ivanova & Jasmins, 2020).

5.2.4. Pronoun Reference

When it comes to Trump's shifting personal pronoun reference, the personal pronoun *I* was solely used for self-references, which often transmitted Trump's feelings. For instance, he often made promises about the future and often felt mistreated by both the opposition and media, although he said he had done nothing wrong. Moreover, Trump often insinuated that he simply did not understand where accusations came from and was very confused, i.e., played ignorant. Therefore, he must have felt that the world around him was trying to block his progress and that it was his job to report on this issue.

In the case of the first-person plural, it could be understood as: grouping Trump and his administration or party; grouping Trump with citizens who follow him; grouping Trump and the nation; being employed as an extension of *I* (meaning a self-reference); or be a referent which excludes Trump through quotation. Trump often said "we" when talking about winning and losing, perhaps because he felt like him winning meant the nation winning and the same happened when he lost, i.e., it was a mistake and a loss for the country. This pronoun is also found in utterances that imply that Trump and his party are doing well against every issue and, even during the pandemic, placing the United States over all other countries. An attack on

Trump is reportedly an attack on a “we”, meaning that Trump felt that “fake news” was a way to destroy the United States, and that citizens should feel angry and defend themselves (by defending him).

The second-person *you* can be found to: refer to specific individuals or groups; to allude to the entire population of a state; employed as a way to address every individual citizen at once; used to address anyone and everyone; and employed to address online followers. While the pronoun *you* was often seen in utterances which meant to insult other people. It also occurred when he mentioned party members he wanted to endorse or people that he really liked, mostly for promoting the values that Trump liked or for creating articles that favoured him. Notably, Trump also mentioned often that he had many friends but also many enemies.

Concerning the third-person singular masculine *he*, it is found to be aimed at specific individuals, from friends to in-group members, but also to address enemies which Trump especially disliked. His use of the pronoun *he* gets assigned a heavy electoral tone, because he endorses all of the party members that follow the values he likes. More interestingly, in both corpora it can be a self-reference through the act of quoting someone else who is talking about Trump (at the time of his tweeting).

The third-person plural *they*, can be seen to refer mainly to the Democrats but also to past administrations; fake news media; American soldiers in foreign ground; European countries; rioters; and citizens of a specific state. This pronoun evidenced how Trump viewed “the other”, who he considered an enemy. It often took the form of the Democrats, which were his opposition and were said to always be planning to impeach and destroy Trump’s image. They are called insane because they were said not to stand for the values that Trump felt were good for the nation. Both the Democrats and the members of past administrations are said to have done very bad things, which set back the nation, creating problems which Trump had to solve before he could fulfil his promises.

Specifically in Corpus 2, Trump vilifies protesters by calling them rioters that threaten the country. Furthermore, in the pandemic scenario, although being a vague expression, the lexeme *they* helped to define who was doing well and who was doing badly against the virus, creating a sort of ranking system, controlled solely by Trump.

5.2.5. Flouting of Maxims

All the data presented and analysed in the previous paragraphs shows the extent to which Trump managed to flout pragmatic maxims to implicate meaning and manipulate citizens' beliefs. The first maxim of quantity is flouted when less information is given than required (Grice, 1975), that is, when Trump could have been more informative if he wanted to. Therefore, it may occur when Trump did not actually know what he was talking about or only had a very small part in whatever action he was mentioning. For instance, Trump always showed himself involved with the solving of the pandemic through the coronavirus task force – because he said he was in all the meetings – but he could never disclose his actual plan to stop the spread of COVID-19 and only insisted that indeed there was a plan, as seen in example 366³⁹. The same strategy is found when he mentioned having a plan for the vaccine, as seen in example 367, or when he mentioned any other plans that he had for the nation.

366. We have a perfectly coordinated and fine tuned plan at the White House for our attack on CoronaVirus

367. Together we are putting into policy a plan to prevent detect treat and create a vaccine ag

Concerning the pandemic, Trump produced almost no informative tweets, although he could have averted citizens to be careful (but chose not to). This means that it was possibly not beneficial for him to do so. His use of promises, like the promise for a vaccine, was found frequently in corpus analysis, yet Trump never explained the steps planned to achieve said goal and did not even make clear if there ever was a defined and solid plan.

Finally, Trump's narrative presented the country as a place with many issues to be solved, but he could never give specific information on these issues or even on how he could be the one to solve them, possibly implying that he did not have a proper plan for these issues and, as such, was unable to solve them.

The 2nd maxim of quantity was flouted when Trump over explained to forcibly justify his wrong doings and also when he clearly blame-shifted to enemies to further avoid commitment. The flouting of the maxim is made even clearer when Trump created a debate with himself in Twitter, trying to justify his actions before anyone could accuse him of something he had done. This often happened through quotes, where he would quote someone insulting him and from there create a large debate with himself (to defend himself). To further

³⁹ These examples do not follow the 80 character limitation, simply because of the filter function, which in this instance is made to reach the full context explained in the paragraph.

support his arguments, Trump would call on the mistakes of the opposition to try and show that although citizens felt like his mistakes were product of bad decision making, the mistakes of the opposition were worse and thus, citizens should rather focus on the enemy that is threatening their lives.

The 1st maxim of quality was often flouted by Trump, particularly when he exaggerated or minimized events, people or objects. His rhetoric was filled with hyperboles, everyone was great, all issues were large and very bad, people were sometimes great and the best and other times big losers, his actions were often big wins with unlimited potential and the actions of his enemies created schemes that were very dangerous for the citizens of the United States. These accusations often lacked the support of evidence and factual information.

The 2nd maxim of quality is flouted, for instance when Trump vilified the Democrats and accused them of scheming against him to ruin his image, but he never provided evidence to support this. In the same light everything the OTHER did was always big lies and fake news, even though there never was any evidence given to support this. The same occurred when Trump mentioned the many people that supported him and the many people that said he was doing a good job. Often these people were not identified, leaving in citizens the feeling that he was clearly lying.

When called out on what he said Trump often insulted and committed social gaffes, flouting the maxim of relation. He insulted both people in specific and in large groups, for instance, Trump often adjectivized Joe Biden as sleepy, perhaps insinuating he was too old to be a worthy opponent, while other times he insulted black citizens protesting, calling them rioters who must be punished for not respecting him.

More often than that, Trump's disdain towards China can be found in both corpora. At first China is simply an economic enemy, which should not be trusted and is taking away from citizens. In the latter corpus (Corpus 2 / during the pandemic), both China and the Chinese are an economic and political enemy and a danger to the health of all citizens. That is so because Trump called COVID-19 the China virus and the Chinese virus (Sousa, Ivanova & Jasmins, 2020), creating fear among citizens and prejudice towards a foreign nation.

The flouting of the maxim of manner follows a pattern awfully similar to the flouting of the maxims of quality, since Trump's lack of evidence made him use vague expressions to support his arguments. Through his mentions of "many" and "millions" of people, Trump

referenced citizens that he did not identify and which became vague sources. This use of vague expressions aimed at creating sources which would identify Trump as worthy of being a national leader by proving that public opinion was favourable towards him. The maxim is also flouted when a speaker fails to be succinct and, although Twitter imposed limitations to the size of tweets, Trump went over them to compile tweet after tweet, connecting them through a double ellipsis (as seen in example 367 above).

5.2.6. Impact on Audiences

For this research it is relevant to understand the potential impact that a president's tweeting habits might have on audiences, especially those that are forced to follow his social media to keep up to date with the pandemic. First, Trump's political rhetoric, knowingly populist, impacted heavily on the daily lives of citizens because his strategy was, in short, to create fear and then be the one to solve it. From the perspective of citizens, the country was flawed and destroying itself slowly, threatening the lives of American who must follow Trump to live. Trump manipulated citizens into believing he was one of them, a soldier, who is also being attacked and also in danger.

American citizens are often left confused, because the threats that Trump identified are always a massive danger to the nation but at the same time, they seemed to be easily solved in just a few steps by Trump. This happened during the pandemic, where COVID-19 was a dangerous weapon in the hands of a foreign nation but, upon infecting American citizens, its danger is easy to solve. Americans are manipulated to also minimize the severity of the crisis because Trump repeatedly stated that they were doing much better than other countries – doing so well that they could help foreign nations.

Trump manipulated what was good and what was bad, forcing citizens to adopt his view, which strategically always made him look good. The same happened with his party members, whom citizens are forced to see as a united front. Although he made many promises in his term and always said to be acting for the best of all citizens, Trump never actually committed to what he said and that made most citizens have a hard time trusting him. Furthermore, when citizens pointed out mistakes, their attention would be diverted to past administrations. This created a divide between American citizens, creating a polarized society.

Donald Trump focused the attention of citizens on “the other”, and the citizens felt both attacked by China when the coronavirus disease started causing deaths and by black citizens

which Trump called rioters. All of this was a strategic ploy to get Americans distracted from the bad management of the crisis and to focus on other (imagined) threats, but that is not where the diversion of attention stops. Repeatedly, Trump would mention both people and groups who were doing something he felt was wrong, therefore coming up with arguments that proved that they would also affect Americans. This happened through his dislike of news stations, the opposition, European countries and even the World Health Organization.

Concerning his ability to communicate clearly, citizens were mostly left with the feeling that he either did not know about the topics he was talking about or played a small role in them. For instance, he could neither explain his plans to prevent COVID-19 nor the vaccine. He was also unable to explain the many issues the country had. His use of insults, over-explanations and vague expressions, could possibly have made citizens believe that he was the party at fault, that he did not commit to what he said and only had his own goals in mind.

6. Final Considerations

Considering the main research question of this piece of research, Trump's pragmalinguistic strategies did not change between the two expectedly different periods. His rhetorical style and hidden agenda did not evidence diverse language features reflecting the pandemic situation or societal difficulties. The former president showed a capability to adapt his strategies to whichever context he was inserted in and, as such, he created opportunities for his own success. He also worked routinely to make his image seem positive, even if what occurred because of his actions or in society in general was negative or grim.

This piece of research benefitted from a corpus-driven approach, since no assumptions were made, allowing for an objective interpretation of data. Furthermore, a corpus-driven approach matched the aims of the study and favoured a thorough look into Trump's rhetorical style, enabling a better understanding of data, particularly the linguistic choices that characterise political rhetoric, populist discourse, subject pronoun shifts, computer-mediated communication and interaction between interlocutors in Twitter.

Furthermore, thanks to computational tools like Wordsmith Tools 8, it was feasible to filter through all the data and extract all relevant parts of the corpora. In a systematic way, this piece of research showed the benefits of departing a study from the frequency list and growing it from the branches that appear relevant, as such slowly building the analysis of Trump's Twitter communication.

This study scrutinized on the different parts-of-speech, achieving a broad view of how Trump organized his thoughts and viewed the world around him. It was found through analysis that pronoun-shifts were common and that enabled a reflection on their role in political rhetoric (considering ingroup and outgroup relations) and opened a way to reflect on how Trump positioned himself according to his needs. Furthermore, vague expressions were evidenced and common in Trump's linguistic choices in Twitter communication, disclosing how he organized his words in a way that enabled a possibility of avoiding commitment in case of conflict and also enabled him to approach topics that otherwise he would not be able to because of a lack of knowledge. These expressions also allowed him to prove points to which he lacked factual evidence. Thus, the data available evidenced how a leader perceived the world around him and how he echoed his goals through his words. Nonetheless, this piece of research established that Trump favoured adapting his own pre-existing strategies rather than changing them, particularly when faced with a global pandemic, as evidenced in the two time-periods contrasted.

Through corpus analysis it was possible to corroborate the conclusions taken by other scholars concerning conceptual metaphor use in politics. Particularly the use of the metaphor of WAR as an answer to COVID-19. It is evidenced in this piece of research that Donald Trump observed COVID-19 as an enemy to be attacked and to defend from, a threat to national security. The metaphor of WAR allowed Trump to keep control over the country and influence the actions of his followers, particularly, because of the context of this research, online interlocutors. In the same fashion, Trump associated COVID-19 with China, playing to his hidden agenda against this foreign nation, dealing with them as an economic and political enemy.

Trump often expressed himself negatively, through criticism and accusations (face-threatening acts; positive face of hearer (Brown & Levinson, 1987). As so he mistreated all those who went against him and his points of view. His violent expressions achieved the same goal, threatening the face of interlocutors. Furthermore, Trump threatened, ordered and warned interlocutors/followers of his Twitter, commanding them to his will (threatening negative face).

This study also contributed to an understanding of how social media can contribute to misinformation, particularly when produced by influencers – political leaders – which are sometimes followed blindly by interlocutors. It contributed to understand how political strategies are used in Twitter to influence and manipulate citizens who are looking for aid and

instructions when faced with a global pandemic. The trust of these citizens is abused and used for a leaders' own goals.

This piece of research was limited by the size of the corpora, which could have been larger, further broadening the context and enabling for further evidence of the conclusions taken, but that would have made it less feasible to complete it, according to the format and requirements of this study. On another note, larger corpora could enable this qualitative research to adopt a more statistically oriented methodology, notably inferential statistic (including the use of chi-square tests, for example in contrasting sets of data). Function words, as opposed to the content words analysed in this research study, are just as relevant but fell outside the scope of this research. Additionally, the analysis of vague expressions could have been expanded to better explain the several subcategories found in these expressions.

Future research could collect all of Trump's Twitter activity and observe/analyse how his strategies evolved through time and through different societal contexts. It would also be of interest to contrast the results of this piece of research with results taken from other world leaders, possibly allowing scholars to find (or not) possible pattern in 21st century political discourse. Observing as social media has played a major role in this piece of research, future work could try to understand if these strategies are heightened by other social media (not just Twitter). It would be particularly interesting to understand if the pragmatolinguistic strategies enlightened in this piece of research, perceived as a case study, were created by Trump and if so, observe if other world leaders, or people running in election, have started to adapt said strategies for their own goals and/or hidden agendas. The analysis done in this research could have been expanded to include the use of, for instance, other content words, such as verbs in Trump's output, likely to be object of my further research. Lastly, this research study focused on the language and interaction at the level of twitter messages; still further studies may draw on other communicative strategies necessarily related to an understanding of political rhetoric which demand a previous study of communication and political science.

Citizens should be able to differentiate between factual and false information and, by their own sake and interest, perceive what their leaders truly mean. The focus on the factual and informative clines in leaders' rhetoric is worthwhile scrutinised, and so is the sort of impact on their interlocutors as well as followers willing to look for information.

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Appendix 1 – Tweet IDs for Corpus 1

1168490496857128960	1169753952130359297	1171014995452321792
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1168493188056829952	1169759456277729282	1171022839962644480
1168493189050896384	1169782689257447424	1171046014234648576
1168493190468558848	1169815874988986369	1171046015106990081
1168496276918480896	1169815875966210049	1171051472689270784
1168499355248205826	1169945439434674176	1171051473607823360
1168499357131427840	1169945440240001025	1171052472938446849
1168644326060122113	1169945441233985536	1171056605233852416
1168644326982901763	1169948497241677824	1171058875220541441
1168663012837904385	1169948967947395072	1171074780566622208
1168663013806792704	1169953150251556864	1171118506089361409
1168874291376656384	1169956429366779904	1171118507712503813
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1168879633984643072	1169967054755172354	1171120177196544000
1168882690713690112	1169981017794535432	1171153468364451845
1168891437032857600	1169981019228913664	1171175113883934720
1168891438324756481	1169981020634013696	1171178388460978177
1168893583283425280	1169982535646031873	1171193903581675524
1169002093476290563	1169983251160731651	1171195460670939136
1169048221026590725	1169992234382610432	1171222442808942593
1169050760098791431	1170097018901020673	1171228988024311809
1169053562904678405	1170123708696072192	1171254828456194049
1169062379134574592	1170123710164013056	1171403065540390912
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1169244729801871360	1170171081853931520	1171413029264732160
1169244730661769216	1170285513376485378	1171429005251104769
1169244732691767296	1170285514324414464	1171431074485817344
1169246982508072960	1170288754520657920	1171439301826994176
1169356701943894017	1170292743865810944	1171452880055746560
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Appendices listed on the CD

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Appendix 1 – Corpus 1 in Word format

Appendix 1.1. – Corpus 1 in simple text format

Appendix 2 – Corpus 2 in Word format

Appendix 2.1. – Corpus 2 in simple text format

II- Frequency Lists

Appendix 3 – Frequency list for Corpus 1

Appendix 4 – Frequency list for Corpus 2

III- Concordance Lines – Nouns

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Appendix 6 – Concordance Lines for *democrats*

Appendix 7 – Concordance Lines for *nothing*

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Appendix 9 – Concordance Lines for *people*

Appendix 10 – Concordance Lines for *Trump*

Appendix 11 – Concordance Lines for *news*

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Appendix 13 – Concordance Lines for *country*

Appendix 14 – Concordance Lines for *Schiff*

Appendix 15 – Concordance Lines for *house*

Appendix 16 – Concordance Lines for *American*

Appendix 17 – Concordance Lines for *time*

Appendix 18 – Concordance Lines for *years*

Appendix 19 – Concordance Lines for *party*

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Appendix 26 – Concordance Lines for *president*

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