NUPRAM - Núcleo de Política, Redes Sociais e Aprendizado de Máquina

“Mapping Political Elites COVID-19 Vaccine Tweets in Brazilian Portuguese in 2020, 2021 and 2022”

Codebook

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I. Introduction

This codebook summarizes the data collection and coding stages employed in developing the *Mapping Political Elites COVID-19 Vaccine Tweets in Brazilian Portuguese* dataset for Version 2.0. The dataset provides detailed information about the participation of Brazilian political elites on Twitter/X in discussions on COVID-19 vaccines and vaccination and updates the corpus used by Barberia et al. (2023). This project is part of the work undertaken by our research team in NUPRAM - *Nucleo de Política, Redes Sociais e Aprendizado de Máquina* or Politics, Social Networks and Machine Learning Research Group.

This codebook has five main sections. The first section introduces the conceptual framework for the study, which seeks to use the SAGE Working Group 3Cs/5Cs/6Cs vaccine hesitancy model to understand the opinions, attitudes, and sentiments concerning COVID-19 vaccines and vaccination. The second section delineates processes undertaken to build the *Political Elites Dataset.* The third section is devoted to outlining major COVID-19 events in 2020-2022. The fourth section explains the project's *COVID-19 Tweet Classification Strategy.* Finally, the fourth and last section presents detailed descriptions of all the variables in the compiled dataset.

The section devoted to the *Political Elites Dataset* aims to provide detailed information on candidates, including their party affiliation during the 2020 municipal election for mayor, and information about active and inactive Twitter profiles and activity on Twitter/X regarding COVID-19 vaccines and vaccination. The *COVID-19 Tweet Classification Strategy* section aims to describe and discuss in detail the steps taken to collect and categorize candidate tweets. Finally, the third section provides detailed information about other variables such as date, likes, retweets, and epidemiological week, as well as descriptions of all the variables in the dataset with details about coding processes.

II. Vaccine Hesitancy: Conceptual Approach

According to the Strategic Advisory Group of Experts (SAGE) of the World Health Organization (WHO), vaccine hesitancy involves delaying acceptance or refusing vaccines despite the availability of vaccination services (MacDonald and SAGE Working Group on Vaccine Hesitancy 2015). Thus, activities associated with vaccination are not restricted to a polarized position, where individuals or groups are either anti-vaccine or pro-vaccine, but rather exist along a continuum from accepting all to refusing all vaccines. This continuum includes categories such as accepting some, delaying some, and refusing some. Vaccine hesitancy attitudes are influenced by various factors that may differently impact the categories within the vaccine hesitancy continuum (Kumar et al. 2016).

SAGE proposed a framework for the factors associated with vaccine hesitancy known as the 3 C’s: complacency, convenience, and confidence. Understanding these factors is crucial for health professionals, researchers, and policymakers to address vaccine hesitancy effectively. Based on the 3Cs approach, the model was enhanced and evolved into the 5Cs model. The 5C model replaces "convenience" with "constraints," which includes structural and psychological barriers related to vaccination intention and uptake, including political and sociocultural barriers and psychological distress. In addition to the original three aspects, it incorporates "risk calculation" and "collective responsibility” (Betsch, Böhm, and Chapman, 2015). Table 1 presents the definition of each C according to initial 3C’s and the 5C’s approaches (MacDonald, 2015).

Table 1. The 3 and 5 C's Model of Vaccine Hesitancy.

3 C’s Model	*Vaccination Confidence*	Defined as trust in (i) the effectiveness and safety of vaccines, (ii) the system delivering them, including the reliability and competence of health services and professionals, and (iii) the motivations of policymakers deciding on necessary vaccines.
3 C’s Model	*Vaccination Complacency*	It occurs when vaccination or a specific vaccine is not considered a necessary preventive action associated with low perceived risks of vaccine-preventable diseases. According to SAGE (2014), “vaccine complacency exists where perceived risks of vaccine-preventable

		diseases are low, and vaccination is not deemed a necessary preventive action.”
3 C’s Model	*Vaccination Convenience*	It is significant when factors such as physical availability, affordability, willingness to pay, geographical accessibility, language and health literacy, and appeal of immunization services affect uptake. The quality of service, both real and perceived, and the degree to which vaccination services are delivered in a time, place, and cultural context that is convenient and comfortable also affect the decision to be vaccinated and could lead to vaccine hesitancy.
5 C’s Model	*Vaccination Risk Calculation*	It refers to the comparison of personal health risks of infection versus vaccination.
5 C’s Model	*Vaccination Collective Responsibility*	It involves the desire and willingness to become vaccinated to protect others or to generate population or herd immunity.

Source: MacDonald & SAGE Working Group, 2015; Betsch, Böhm, and Chapman, 2015.

Other conceptual approaches have been utilized, generally encompassing the aspects addressed by the 3 and/or 5Cs. Thomson et al. (2016) discussed the 5As related to vaccine hesitancy, where *access* is “the ability of individuals to be reached by, or to reach, recommended vaccines”; *affordability*, “the ability of individuals to afford vaccination, both in terms of financial and non-financial costs”; *awareness*, “the degree to which individuals have knowledge of the need for, and availability of, recommended vaccines and their objective benefits and risks”; *acceptance*, “the degree to which individuals accept, question or refuse vaccination”; and *activation*, “the degree to which individuals are nudged towards vaccination uptake.” Comparing both approaches, it is possible to link “access” and “affordability” to convenience, awareness of complacency and risk calculation, and acceptance and activation of complacency and collective responsibility. Other associations can be made to understand COVID-19 vaccine hesitancy.

As presented above, vaccine hesitancy results in non-adherence to vaccination, although, in many cases, this stance can be altered if the triggering factor of the hesitation is addressed. This could include providing information that allows the individual to gain confidence in the vaccine or facilitating access to the vaccine, thereby making it more accessible. Thus, a hesitant stance, when declared, such as in a tweet, is considered unfavorable towards vaccination. In this sense, as will be seen below, tweets that depict any level of hesitation are classified as unfavorable towards vaccination in this study.

Considering the purposes of the project and the conceptual similarity between "complacency" and "risk" calculation, as presented in Table 1, we adopted in this project, when pertinent, the classification of tweets according to the following factors: confidence, complacency, convenience, collective responsibility.

III. Political Elites Dataset

The *Political Elites Dataset* was designed to include detailed information regarding mayoral candidates who participated in the 2020 municipal elections in the Brazilian state capitals. Using the data recorded by the Superior Electoral Court (TSE),[1] we compiled a comprehensive list of all the mayoral candidates who participated in the 2020 elections across the 26 state capitals of Brazil.

Among the 323 candidacies presented in these municipalities, the TSE accepted 300 candidates. The remaining 23 candidates either resigned their candidacies or were rejected by the court. On average, about 12 candidates participated in the elections in each capital. Rio Branco, the capital of the Acre (AC) state, had the lowest candidacies, with only seven competitors at the time of the election. Belo Horizonte (Minas Gerais - MG), Curitiba (Paraná - PR), and Porto Velho (Rondônia - RO) emerged as the capitals with the highest number of candidates, each boasting a total of 15 contenders. Table 1 portrays the number of approved candidacies by the TSE in the 26 Brazilian state capitals.

Table 2. Number of Mayoral Candidates in the 2020 Elections by State Capital

State	City	Number of candidates
Acre (AC)	Rio Branco	7
Alagoas (AL)	Maceió	10

[1] Tribunal Superior Eleitoral (the electoral court of all Brazilian elections). The website can be accessed in: https://www.tse.jus.br/#/

Amazonas (AM)	Manaus	11
Amapá (AP)	Macapá	10
Bahia (BA)	Salvador	9
Ceará (CE)	Fortaleza	10
Espírito Santo (ES)	Vitória	13
Goiás (GO)	Goiânia	14
Maranhão (MA)	São Luís	10
Minas Gerais ()MG	Belo Horizonte	15
Mato Grosso do Sul (MS)	Campo Grande	13
Mato Grosso (MT)	Cuiabá	8
Pará (PA)	Belém	12
Paraíba (PB)	João Pessoa	14
Pernambuco (PE)	Recife	9
Piauí (PI)	Teresina	12
Paraná (PR)	Curitiba	15
Rio de Janeiro (RJ)	Rio de Janeiro	13
Rio Grande do Norte (RN)	Natal	13
Rondônia (RO)	Porto Velho	15
Roraima (RR)	Boa Vista	10
Rio Grande do Sul (RS)	Porto Alegre	11
Santa Catarina (SC)	Florianópolis	10
Sergipe (SE)	Aracaju	11
São Paulo (SP)	São Paulo	13
Tocantins (TO)	Palmas	12

Candidate Biographical Data

For all the candidacies approved by the TSE, we collected information regarding the electoral district, demographic characteristics, party affiliation, education, profession, and electoral performance. Demographic characteristics include the candidate's gender, education, and profession as filed in the TSE candidate official registry records. We also collected data on party affiliation and coalition membership during the 2020 election.

In the TSE database, candidates must provide their educational background according to whether they have an incomplete elementary school, complete elementary school, incomplete high school, or complete high school. In addition, we also recorded the profession each candidate stated when they registered their candidacy with the TSE. Table 3 summarizes the percentage of candidates in 2020 who declared they were professionals working in a health-related field in each city. The health-related professional occupations informed included doctor, dentist, psychologist, speech therapist, or pharmacist. There were candidates with a health-related profession occupation expressed in a total of 17 candidates (10 physicians, four psychologists, 1 speech therapist, 1 dentist and 1 pharmacist). None of the candidates appointed nurses as a declared professional before the election of 2020. Only two won the mayoral election (Alvaro Dias in Natal and Cinthia Ribeiro in Palmas).

Table 3. Percentage of Mayoral Candidates in the 2020 Elections by State Capital

State	City	Percentage of candidates in a health-related field
Acre (AC)	Rio Branco	0%
Alagoas (AL)	Maceió	0%
Amazonas (AM)	Manaus	0%
Amapá (AP)	Macapá	20% (2 candidates)
Bahia (BA)	Salvador	11% (1 candidate)
Ceará (CE)	Fortaleza	10% (1 candidate)
Espírito Santo (ES)	Vitória	0%
Goiás (GO)	Goiânia	0%
Maranhão (MA)	São Luís	0%
Minas Gerais ()MG	Belo Horizonte	0%
Mato Grosso do Sul (MS)	Campo Grande	8% (1 candidate)
Mato Grosso (MT)	Cuiabá	0%

Pará (PA)	Belém	9% (1 candidate)
Paraíba (PB)	João Pessoa	14% (2 candidates)
Pernambuco (PE)	Recife	0%
Piauí (PI)	Teresina	8% (1 candidate)
Paraná (PR)	Curitiba	20% (3 candidates)
Rio de Janeiro (RJ)	Rio de Janeiro	0%
Rio Grande do Norte (RN)	Natal	8% (1 candidate)
Rondônia (RO)	Porto Velho	0%
Roraima (RR)	Boa Vista	0%
Rio Grande do Sul (RS)	Porto Alegre	9% (1 candidate)
Santa Catarina (SC)	Florianópolis	10% (1 candidate)
Sergipe (SE)	Aracaju	0%
São Paulo (SP)	São Paulo	0%
Tocantins (TO)	Palmas	17% (2 candidates)

Classification of Party Alignment with Jair Bolsonaro Government

To measure the positions of parties relative to Bolsonaro´s government, we decided to construct a government/opposition measure using the data provided by "Radar do Congresso."[2] This data measures the votes of each parliamentary in the Legislative Chamber (first house) and Senate (second house). With this, they obtained means for the parliamentarians' votes of each party and compared it with the position of Bolsonaro´s government.

This results in a percentage of how often each party votes with the President's party or his propositions. This percentage ranges from 0% to 100%, indicating how often a party's parliamentarians had positions similar to Bolsonaro´s government positions in Congressional voting.

[2] "Radar do Congresso" is a production of the "Congresso em Foco" with financial support from Google. The website can be accessed here: https://radar.congressoemfoco.com.br/parlamentares/senado. During Bolsonaro´s government (2019-2023) they used the data to produce analyses of governism. Now, the website contains just information about the Lula's government (2023-), but varies analyses can be accessed in the Congresso em Foco website: https://congressoemfoco.uol.com.br/

Following this classification for each party with Congressional representation between 2019 and 2020, constructed by the "Radar do Congresso,"[3] We decided to divide into groups based on each party's percentage. A government party voted with Bolsonaro´s government with more than 80% of the legislative votes. A neutral party voted with the government between 50% and 80% of the time. An opposition party voted less than 50% of the legislative votes with the government. Table 4 reports the percentage of votes for each party aligned with the Bolsonaro government between 2019 and 2020 in parentheses and whether they were classified as government, neutral, or opposition.

Table 4. Party's Alignment (%) with Bolsonaro Government

Party	**Government/Opposition Position**
PSL (97%), Patriota (94%), DEM (93%), PSC (93%), NOVO (92%), PSDB (92%), MDB (91%), PP (91%), Republicanos (91%), PL (90%), PSD (90%), PTB (90%), SD (89%) and Cidadania (87%).	Government Party
Podemos (77%), Pros (75%), Avante (74%) and PV (68%)	Neutral Party
PDT (48%); PSB (46%); Rede (36%); PCdoB (29%); PT (20%) and PSOL (15%)	Opposition Party

Source: Radar do Congresso (2020)

Classification of Candidates Aligned or Endorsed by Jair Bolsonaro

We classified candidates' alignment with then-president Jair Bolsonaro during the election campaign period in 2020. We created two distinct variables: "*endorse_president*" and "*align_president.*" To obtain evidence of formal political alignment, we consulted the candidate's social media accounts (Twitter, Facebook, and Instagram), news sites, and interviews. The posts made during 2020 that were identified as aligned with Bolsonaro were verified. Using Google's search engine, we also searched for the names of the candidates and keywords such as "is supported by the president/Bolsonaro" or "supports/is aligned with the president/ Bolsonaro."

[3] We used the information published in this article to classified the parties into group of governism, considerer the percentage of similar votes with the Bolsonaro´s government: https://congressoemfoco.uol.com.br/area/governo/exclusivo-os-12-partidos-que-formam-a-base-fiel-do-governo-na-camara/

The variable “*endorse_president*” refers to candidates Bolsonaro publicly endorsed during the 2020 mayoral elections campaign. These candidates received official support from Bolsonaro through television, radio, social networks, or other mass media endorsements.

Of the 300 candidacies presented, only 11 candidates, spanning across different parties, received endorsements from Jair Bolsonaro. Except for Sebastião Bocalom (PP/Rio Branco-AC), all candidates endorsed by the former president were defeated at the polls.

The variable “*align_president*” refers to those candidates who, despite not receiving a formal endorsement from Bolsonaro during the 2020 campaign, declared that, if elected, they would govern following the policies and guidelines adopted at the national level by Bolsonaro. Only candidates who declared themselves aligned with the Bolsonaro government were classified as such.

Among the candidates who expressed alignment with Jair Bolsonaro but did not receive his official endorsement, we identified 48 individuals who based their campaigns on the former president's ideology and an additional 11 whom he endorsed. These 59 candidates, aligned with or supported by the former president, utilized Bolsonaro's image during the 2020 elections as part of their campaigns in promotional materials, including flyers and campaign promotional materials. Table 5 summarizes the candidates who supported or aligned with Jair Bolsonaro in the 2020 municipal elections.

Table 5. Candidates Endorsed* or Aligned with Jair Bolsonaro in the 2020 Municipal Elections by State Capital.

State	Capital	Candidate endorsed or aligned with Bolsonaro (Party)
AC	Rio Branco	Roberto Duarte (MDB)* Sebastião Bocalom (PP)*
AL	Maceió	Josan Leite (PATRIOTA)
AM	Manaus	Capitão Alberto Neto (REPUBLICANOS) Coronel Menezes (PATRIOTA)* Chico Preto (DC) Romero Reis (NOVO)

AP	Macapá	Cirilo Fernandes (PRTB) Guaracy Júnior (PSL) Haroldo Iram (PTC) José Alcolumbre (DEM)* Patrícia Ferraz (PODE)
BA	Salvador	Cézar Leite (PRTB)
CE	Fortaleza	Heitor Freire (PSL) Capitão Wagner (PROS)*
ES	Vitória	Halpher Luiggi (PL) Delegado Pazolini (REPUBLICANOS) Capitão Assumção (PATRIOTA)
GO	Goiânia	Gustavo Gayer (DC) Major Araújo (PSL) Vanderlan Cardoso (PSD)
MA	São Luís	Eduardo Braide (PODE) Sílvio Antônio (PRTB)
MG	Belo Horizonte	Bruno Engler (PRTB)* Lafayette Andrada (REPUBLICANOS)
MT	Cuiabá	Roberto França (PATRIOTA)*
PA	Belém	Delegado Federal Eguchi (PATRIOTA)* Guilherme Lessa (PTC) Vavá Martins (REPUBLICANOS)
PB	João Pessoa	Nilvan Ferreira (MDB) Wallber Virgolino (PATRIOTA)
PE	Recife	Coronel Feitosa (PSC) Mendonça Filho (DEM) Delegada Patrícia (PODE)*
PI	Teresina	Major Diego Melo (PATRIOTA)
PR	Curitiba	Fernando Francischini (PSL) Zé Boni (PTC) Marisa Lobo (AVANTE)
RJ	Rio de Janeiro	Luiz Lima (PSL) Marcelo Crivella (REPUBLICANOS)*
RN	Natal	Coronel Azevedo (PSC) Coronel Hélio Oliveira (PRTB) Delegado Leocádio (PSL)

RO	Porto Velho	Sargento Eyder Brasil (PSL)
RR	Boa Vista	Antônio Nicoletti (PSL) José Ottaci (SOLIDARIEDADE)
RS	Porto Alegre	Gustavo Paim (PP)
SC	Florianópolis	Alexander Brasil (PRTB) Hélio Bairros (PATRIOTA)
SE	Aracaju	Delegada Danielle (CIDADANIA) Georlize Oliveira (DEM) José Almeida (PRTB) Lúcia Flávio (AVANTE) Delegado Paulo Márcio (DC) Rodrigo Valadares (PTB)
SP	São Paulo	Celso Russomanno (REPUBLICANOS)*
TO	Palmas	Eli Borges (SOLIDARIEDADE) Gil Barison (REPUBLICANOS) Dr. Joaquim Rocha (PMB)

Notes: * President Jair Bolsonaro formally endorsed these candidates.

The average number of candidates declaring alignment with Jair Bolsonaro in each municipality was about two. Among them, the city of Aracaju (SE) stood out with the highest number of candidates linked to the former president, totaling six competitors in 2020. Interestingly, the city of Campo Grande (MS) was the only one in the sample with no candidate aligned with Bolsonaro.

2020 Electoral Results of Candidates

Electoral performance data includes i) votes by candidate in the first and second rounds;[4] ii) a dichotomous variable indicating whether a candidate disputed the second round of election (1 is attributed to cases where the candidate disputed the second round of elections, 0 if not); iii) a dichotomous variable indicating whether the candidate won the

[4] In Brazilian municipal elections, candidates win in the first round if they gather 50%+1 votes. In cases where no candidate accumulates enough votes, a second round is performed, including only the two best positioned candidates in the first round.

election (1 if winner, 0 if not); iv) for winning candidates, the margin of victory, and, v) a dichotomous variable identifying incumbents (1 if incumbent, 0 if not).

In the 2020 elections, 7 of 26 mayors received a majority share in the first round and, therefore, did not have to face a runoff in the second round. Table 6 shows the winner for each capital, the round of victory, and the margin of victory between the first and second place for candidates in the 26 state capitals.

Table 6. Capital Elections Winners and Margins of Victory (%) in 2020

State	Capital	Name of Elected Mayor (Party)	Round of Victory	Margin of Victory between 1st and 2nd place
AC	Rio Branco	Sebastião Bocalom (PP)	2	25.86%
AL	Maceió	João Henrique Caldas (PSB)	2	17.27%
AM	Manaus	David Almeida (AVANTE)	2	2.55%
AP	Macapá	Antônio Furlan (CIDADANIA)	2	11.34%
BA	Salvador	Bruno Reis (DEM)	1	45.34%
CE	Fortaleza	José Sarto (PDT)	2	3.38%
ES	Vitória	Lorenzo Pazolini (REPUBLICANOS)	2	17.00%
GO	Goiânia	Luiz Maguito Vilela (MDB)	2	5.21%
MA	São Luís	Eduardo Braide (PODE)	2	11.06%
MG	Belo Horizonte	Alexandre Kalin (PSD)	1	53.41%
MS	Campo Grande	Marcos Trad (PSD)	1	50.06%
MT	Cuiabá	Emanuel Pinheiro (MDB)	2	2.29%
PA	Belém	Edmilson Rodrigues (PSOL)	2	3.53%
PB	João Pessoa	Cícero Lucena (PP)	2	6.33%
PE	Recife	João Campos (PSB)	2	12.54%
PI	Teresina	José Pessoa (MDB)	2	24.63%
PR	Curitiba	Rafael Greca (DEM)	1	46.48%
RJ	Rio de Janeiro	Eduardo Paes (DEM)	2	28.14%

RN	Natal	Álvaro Dias (PSDB)	1	42.20%
RO	Porto Velho	Hildon Chaves (PSDB)	2	8.90%
RR	Boa Vista	Arthur Henrique (MDB)	2	70.72%
RS	Porto Alegre	Sebastião Melo (MDB)	2	9.26%
SC	Florianópolis	Gean Loureiro (DEM)	1	35.33%
SE	Aracaju	Edvaldo Filho (PDT)	2	15.71%
SP	São Paulo	Bruno Covas (PSDB)	2	18.76%
TO	Palmas	Cínthia Ribeiro (PSDB)	1	21.73%

If we consider all the incumbent candidates (candidates serving their first terms as mayor during the 2020 elections), the number of incumbents is 13, with 10 of them reelected to a second term. These candidates are identified by a dichotomous incumbent variable (0 for candidates not seeking reelection and 1 for candidates pursuing a second term). The incumbents seeking reelection and the outcome of the 2020 election are listed in Table 7.

Table 7. Incumbent Mayors seeking Reelection and 2020 Re-election Outcomes

State	Capital	Name of the Incumbent (Party)	Electoral Result
AC	Rio Branco	Maria do Socorro Neri (PSB)	Not reelected
MG	Belo Horizonte	Alexandre Kalil (PSD)	Reelected
MS	Campo Grande	Marcos Trad (PSD)	Reelected
MT	Cuiabá	Emanuel Pinheiro (MDB)	Reelected
PR	Curitiba	Rafael Greca (DEM)	Reelected
RJ	Rio de Janeiro	Marcelo Crivella (REPUBLICANOS)	Not reelected
RN	Natal	Álvaro Dias	Reelected
RO	Porto Velho	Hildon Chaves (PSDB)	Reelected
RS	Porto Alegre	Nelson Marchezan Júnior (PSDB)	Not reelected
SC	Florianópolis	Gean Loureiro (DEM)	Reelected

SE	Aracaju	Edvaldo Filho (PDT)	Reelected
SP	São Paulo	Bruno Covas (PSDB)	Reelected
TO	Palmas	Cínthia Ribeiro (PSDB)	Reelected

Bolsonaro 2018 Electoral Results in each capital

The *Political Elites Dataset* further includes information about the electoral results for each capital obtained by elected president Jair Bolsonaro in the 2018 presidential elections. While a dichotomous variable (*bolsonaro_municipality_victory*) is employed to signal Bolsonaro´s victory in a particular location, the respective margins of victory in the second round of elections (*margin_victory_bolsonaro*) are also included in the dataset.[5] Table 8 exhibits 2018 electoral results and the respective margins of victory (or defeat) for Bolsonaro in all Brazilian state capitals.

Table 8. Electoral Results and Victory Margins in the 2nd Round for Jair Bolsonaro in the 2018 Presidential Elections for all state capitals

State	Capital	2nd Round Margin	Bolsonaro 2018 Electoral Result
AC	Rio Branco	65.54%	Won
AL	Maceió	23.26%	Won
AM	Manaus	31.44%	Won
AP	Macapá	10.30%	Won
BA	Salvador	-37.18%	Lost
CE	Fortaleza	-11.22%	Lost
ES	Vitória	26.38%	Won
GO	Goiânia	48.40%	Won
MA	São Luís	-15.56%	Lost
MG	Belo Horizonte	31.18%	Won
MS	Campo Grande	42.54%	Won

[5] The 2018 presidential election was decided in the second round. The candidate defeated was Fernando Haddad (PT). In the first round, Bolsonaro, in the first position, had 46.03% of votes, followed by Haddad who had 29.28%. In the second round, Bolsonaro won after having 55.13% of votes against 44.87% of Haddad.

MT	Cuiabá	33.88%	Won
PA	Belém	9.86%	Won
PB	João Pessoa	9.60%	Won
PE	Recife	-5.00%	Lost
PI	Teresina	-25.46%	Lost
PR	Curitiba	53.08%	Won
RJ	Rio de Janeiro	32.70%	Won
RN	Natal	5.96%	Won
RO	Porto Velho	37.88%	Won
RR	Boa Vista	57.22%	Won
RS	Porto Alegre	13.70%	Won
SC	Florianópolis	29.72%	Won
SE	Aracaju	-5.52%	Lost
SP	São Paulo	20.76%	Won
TO	Palmas	29.76%	Won

Considering the 26 state capitals, Bolsonaro received the majority vote share in 20 capitals and lost in 6 others in the 2nd round of the 2018 election. The margin of victory in the municipalities he won varied from 65.54% in Rio Branco to 5.96% in Natal. In the municipalities he lost, the loss margin varied from -37.18% in Salvador to -5.00% in Recife.

Twitter ID Retrieval

Based on data registered in the TSE (Superior Electoral Court) of candidates running for mayor positions in the 2020 elections in the 26 state capitals of Brazil was used to locate active Twitter accounts used by these candidates within the research period. Of the 295 candidates, we could not identify a Twitter account for 37 (12,5% of all candidates) of these candidates. Table 9 presents the candidates, 258 of whom had a Twitter account and the 37 without a Twitter account in 2020. In all state capitals, there were candidates with an active

Twitter account. The capitals with candidates without an active Twitter account were Salvador (BA), São Luiz (MA), Rio de Janeiro (RJ), and Porto Alegre (RS).

Table 9. Mayoral candidates in 2020 from the 26 state capitals with and without active Twitter accounts

State	Capital	Candidates with active Twitter accounts	Candidates without Twitter accounts
AC	Rio Branco	Tião Bocalom; Daniel Zen; Jamyl Asfury; Minoru Kinpara; Roberto Duarte; Socorro Neri	Belcladio Jarbas Soster
AL	Maceió	Alfredo Gaspar de Mendonça; Corintho Campelo; Cicero Filho; Davi Davino Filho; Jhc; Lenilda Luna; Valeria Correia; Ricardo Barbosa	Josan Leite Pereira Barros; José Cícero Soares de Almeida
AM	Manaus	Amazonino Mendes; Capitão Alberto Neto; Coronel Menezes; Chico Preto; David Almeida; Marcelo Amil; Ricardo Nicolau; Romero Reis; Alfredo Nascimento; Zé Ricardo	Gilberto Vasconcelos da Silva
AP	Macapá	Cirilo Fernandes; Dr. Furlan; Haroldo Iram; Josiel; Patrícia Ferraz; Paulo Lemos; Gianfranco; Professor Marcos	João Alberto Rodrigues Capiberibe; Guaracy Batista da Silveira Júnior
BA	Salvador	Bruno Reis; Rodrigo Pereira; Celsinho Cotrim; Cezar Leite; Bacelar; Hilton Coelho; Major Denice; Olívia; Pastor Sargento Isidório	-
CE	Fortaleza	Capitão Wagner; Célio Studart; Paula Colares; Heitor Férrer; Heitor Freire; Luzianne Lins; Anizio; Renato Roseno; Sarto	Samuel Moraes Braga
ES	Vitória	Capitão Assumção; Coronel Nylton; Gandini; João Coser; Mazinho; Namy Chequer; Neuzinha; Sergio Sá	Eron Domingos Souza Lima; Gilberto Batista Campos; Halpher Luiggi Monico Rosa; Lorenzo Silva de Pazolini; Raphael Góes Furtado

GO	Goiânia	Delegada Adriana Accorsi; Alysson Lima; Major Araújo; Elias Vaz; Fábio Junior; Gustavo Gayer; Maguito Vilela; Manu Jacob; Samuel Almeida; Talles Barreto; Vanderlan Cardoso; Virmondes Cruvinel	Antônio Vieira Neto; Cristiano de Moraes Cunha
MA	São Luís	Bira; Duarte; Eduardo Braide; Hertz Dias; Jeisael; Neto Evangelista: Professor Franklin; Rubens Junior; Silvio Antonio; Yglésio Moyses	-
MG	Belo Horizonte	Alexandre Kalil; Áurea Carolina; Luisa Barreto; Bruno Engler; Fabiano Cazeca; João Vitor Xavier; Lafayette Andrada; Marcelo Souza e Silva; Marília Domingues; Nilmário Miranda; Rodrigo Paiva; Wadson Ribeiro; Wanderson Rocha; Professor Wendel Mesquita; Cabo Xavier	-
MS	Campo Grande	Dagoberto; Márcio Fernandes; Esacheu Nascimento; Guto Scarpanti; João Henrique; Marcelo Bluma; Marquinhos Trad; Vinícius Siqueira; Paulo Matos; Pedro Kemp	Cristiane Pinheiro Duarte; Ednei Marcelo Miglioli; Sidnéia Catarina Tobias
MT	Cuiabá	Aécio Rodrigues; Gilberto Lopes Filho; Emanuel Pinheiro; Paulo Henrique Grando; Gisela Simona	Abilio Jacques Brunini Moumer; Julier Sebastião da Silva; Roberto França Auad
PA	Belém	Cássio Andrade; Cléber Rabelo; Delegado Federal Eguchi; Thiago Araújo; Edmílson Rodrigues; Gustavo Sefer; Priante; Vavá Martins	José Jerônimo de Sousa; Luiz Guilherme Lessa de França; Jair Lopes Correia; Mário Couto Filho
PB	João Pessoa	Anísio Maia; Camilo Duarte; Cícero Lucena; Edilma Freire; Ítalo Guedes; Nilvan Ferreira; Raoni; Ricardo Coutinho; Ruy Carneiro; Wallber Virgolino	Carlos Antônio Araújo Monteiro; João Almeida de Carvalho Junior; Rafael Freire Santana; Severina dos Ramos Silva Dantas

PE	Recife	Cláudia Ribeiro; Coronel Feitosa; João Campos; Marília Arraes; Mendonça Filho	Carlos Antonio Gomes de Andrade Lima; Charbel Elias Maroun; Patricia de Oliveira Domingos; Thiago de Oliveira Santos
PI	Teresina	Dr. Pessoa; Fábio Novo; Fábio Abreu; Gessy Fonseca; Fábio Sérvio; Gervásio Santos; Kleber Montezuma; Lucineide Barros; Major Diego Melo; Major Rogério	Pedro Laurentino Reis Pereira; Simone Pereira de Farias Araujo
PR	Curitiba	Camila Lanes; Christiane Yared; Dr. João; Guilherme do Novo; Eloy Casagrande; Fernando Francischini; Goura; João Arruda; Letícia Lanz; Marisa Lobo; Professor Mocellin; Paulo Opuszka; Rafael Greca; Zé Boni	Caroline Arns de Santa Cruz Arruda; Samara Garrantini
RJ	Rio de Janeiro	Cyro Garcia; Benedita da Silva; Delegada Martha Rocha; Clarissa Garotinho; Eduardo Paes; Glória Heloiza; Marcelo Crivella; Bandeira de Mello; Paulo Messina; Luiz Lima; Renata Souza; Fred Luz; Suêd Haidar	-
RN	Natal	Álvaro Dias; Coronel Azevedo; Carlos Alberto (Beto); Coronel Hélio Oliveira; Hermano Morais; Kelps Lima; Delegado Leocádio; Nevinha Valentim; Jaidy Oliver; Rosália Fernandes; Senador Jean	Afrânio Ferreira de Miranda Filho; Fernando Carvalho de Freitas
RO	Porto Velho	Leonel Bertolin; Dr. Breno Mendes; Hildon Chaves; Sargento Eyder Brasil; Ramon Cujui; Vinícius Miguel	Cristiane Lopes da Luz Bernarrosh; Edvaldo Rodrigues Soares; Geneci Gonçalves dos Santos; Leonardo Severo da Luz Neto; Lindomar Barbosa Alves; Mauro Ronaldo Flores Correa; Nascimento Antônio da Silva; Samuel Costa Menezes; Williames

			Pimentel de Oliveira
RR	Boa Vista	Arthur Henrique; Nicoletti; Shéridan; Fábio Almeida; Gerlane; Linoberg; Luciano Castro; Ottaci	Isamar Pessoa Ramalho; Shaolyn Gomes Bezerra
RS	Porto Alegre	Fernanda Melchionna; Gustavo Paim; João Derly; Juliana Brizola; Julio Flores; Manuela; Nelson Marchezan Júnior; Rodrigo Maroni; Montserrat Martins; Sebastião Melo; Valter	-
SC	Florianópolis	Alexander Brasil; Angêla Amin; Dr. Ricardo; Gabriela Santetti; Gean Loureiro; Orlando; Pedrão; Professor Elson	Helio Cesar Bairros; Jair Fernandes de Aguiar Ramos
SE	Aracaju	Alexis Pedrão; Delegada Danielle; Almeida Lima; Rodrigo Valadares; Edvaldo; Georlize; Juraci Nunes; Márcio Macedo; Delegado Paulo Márcio	Gilvani Alves dos Santos; Lúcio Flávio Miranda da Rocha
SP	São Paulo	Andrea Matarazzo; Arthur do Val Mamãe Falei; Bruno Covas; Celso Russomanno; Guilherme Boulos; Jilmar Tatto; Joice Hasselmann; Levy Fidelix; Marcio França; Marina Helou; Orlando Silva; Vera	Antônio Carlos Silva
TO	Palmas	Alan Barbiero; Barison; Cinthia Ribeiro; Eli Borges; Professor Bazolli; Marcelo Lelis; Professor Júnior Geo; Thiago Amastha Andrino; Vanda Monteiro	João Heldes Vilela; Joaquim Rocha Pereira; Max Dornellys Borges de Oliveira

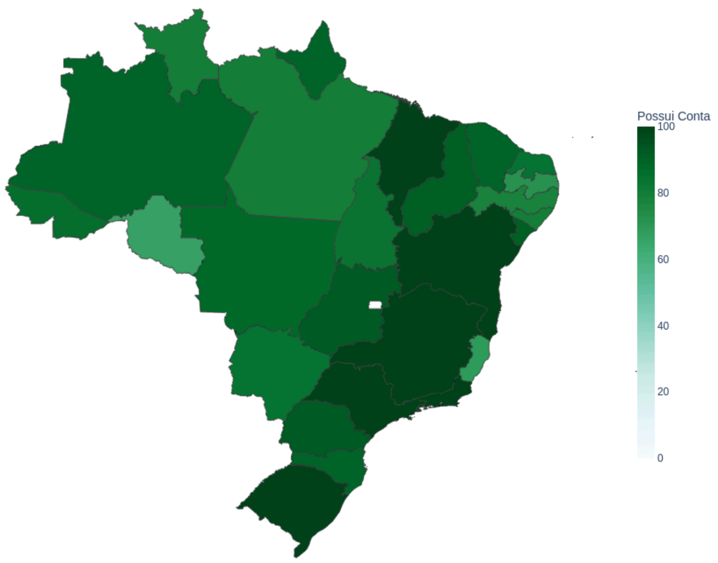
Beyond looking at what candidates had Twitter accounts or not, we also checked at what time the candidate made their last post on its account. Table 10 shows the results of the profile collection. This table was made by looking at the last post made by the candidate in their profile and saving the year. Later, we shall present a more refined metric, using the volume of publications and calculating the 'survival' of accounts in our dataset using the last month of publication.

Table 10. Candidates' Active Profiles on X/Twitter

Scope	Result	Total	Percentage
Did the individual have an account?	Yes	258	87,5%
	No	37	12,5%
Was the individual actively posting tweets during 2020-2023?	Yes	206	69,8%
	No	89	30,2%
Was the individual active in 2024?	Yes	152	51,5%
	No	143	48,5%

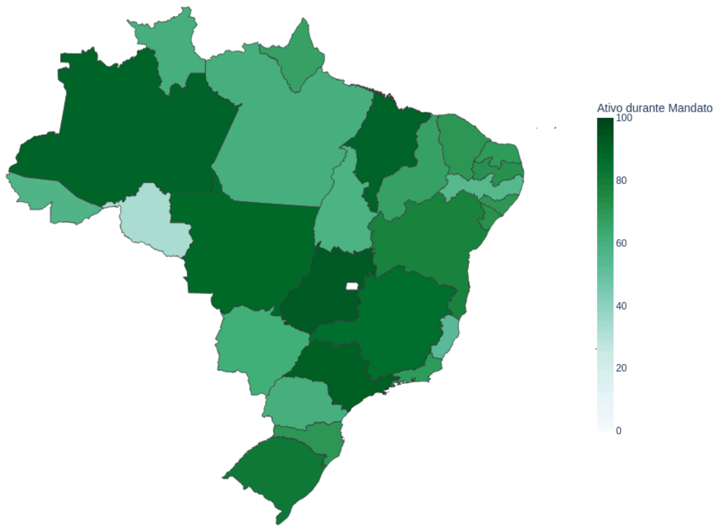
Most candidates have Twitter accounts (87,5%). However, we can see that the activity on the profiles steadily decreases over the duration of the term (2020 to 2024). Only 69,8% of the candidates were active during the entire three year period. Moreover, the percentage of candidates who are still active in 2024 is only 51,5%, a little more than half the initial group of 300 candidates. Figure 1 shows the distribution of individuals who had an account in each state of the Brazilian federation.

Figure 1. Distribution of Sample with an Account by State



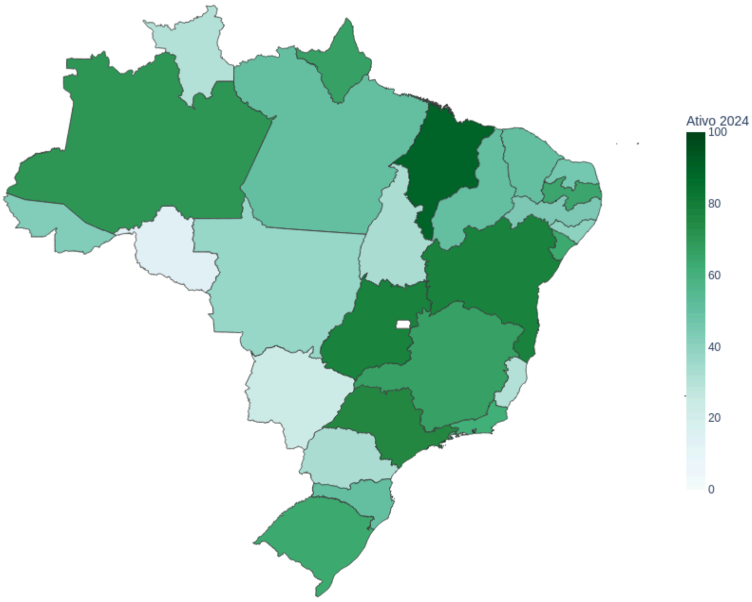
In this scope, there’s little variation in the adoption of Twitter by the Brazilian mayoral candidates. However, the picture changes when we look at the distribution of profiles that were active during the term period (2020-2024). Figure 2 shows that distribution.

Figure 2. Geographical distribution of accounts active on 2020-2023



Although there is no clear division between the cities with the most decrease of active accounts, we can see that some smaller cities in regions that are sparsely populated seem to have the most decrease of activity. Finally, Figure 3 shows the distribution of accounts that are still active in 2024.

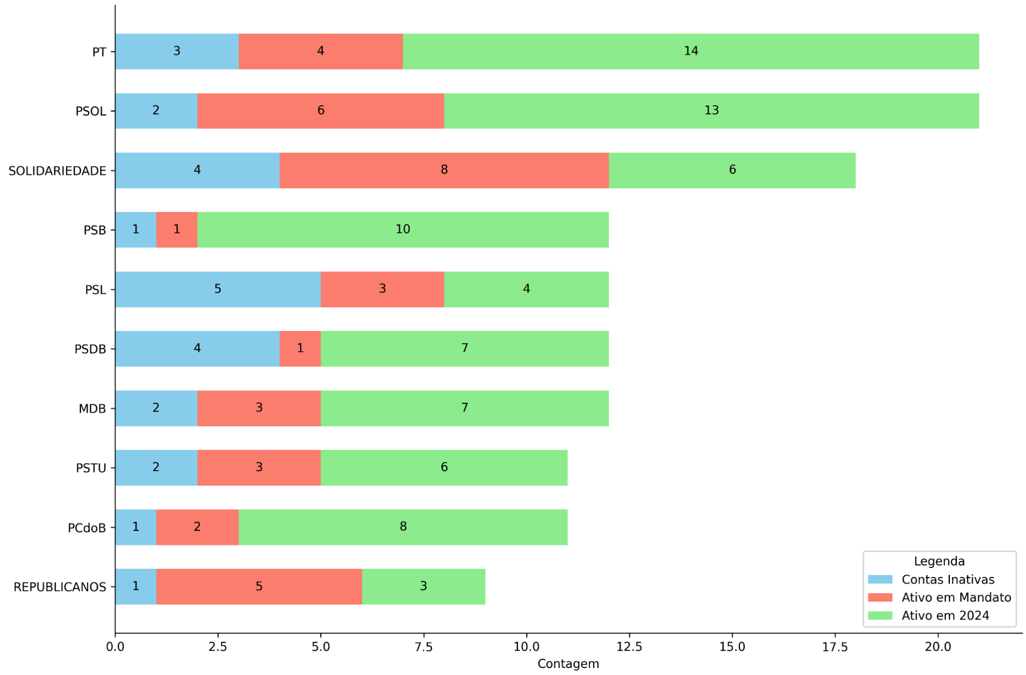
Figure 3. Geographical distribution of accounts active in 2024



Here, the concentration of active profiles seem to converge on the more populated coastal cities, with a sharp decrease of active accounts on most of the inland regions, with some reaching 0% of activity for this year. With these figures we can see that the inequality on activity lies both in time and space, and this has to be taken into account when we look at the results of the annotation of tweets. There is a clear concentration of profiles in some specific regions, and these are the politicians most represented in the dataset.

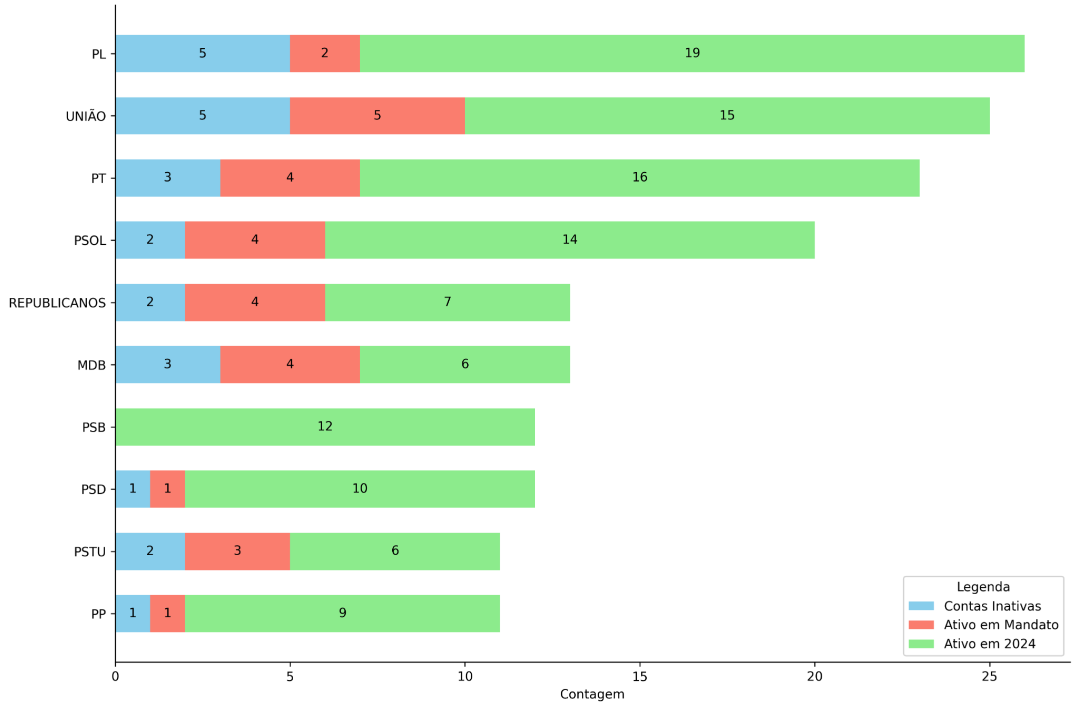
With respect to the ideological and partisan differences of the individuals in the sample, Figure 4 shows the distribution of active profiles in the 10 parties with more candidates overall, using the party of the candidate when he ran for election.

Figure 4. Profile activity on the 10 parties with more candidates



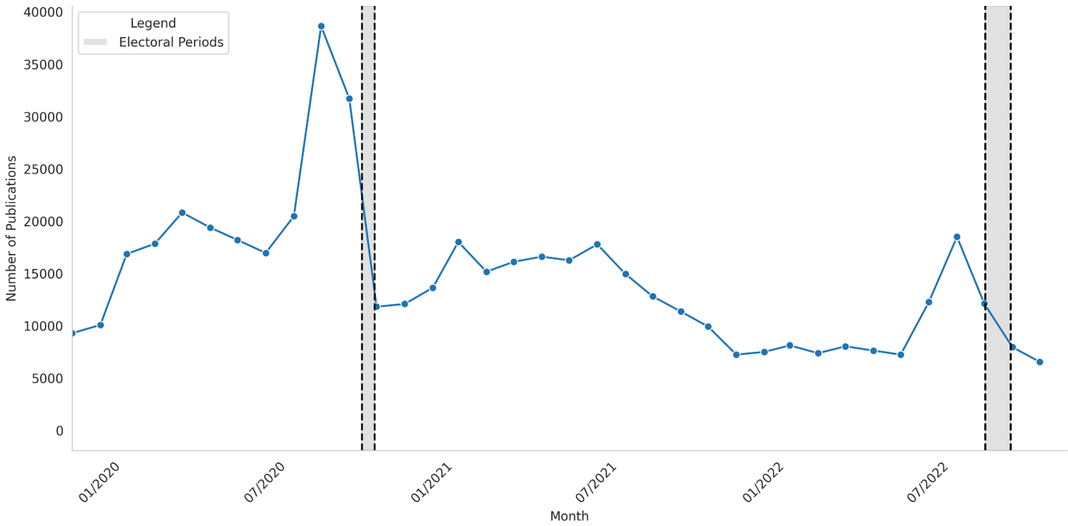
In blue, we can see the number of candidates that, although had accounts on twitter, were inactive in the whole period of 2020 to 2024. In Red, we see the number of candidates that were active during 2020 to 2023, but are inactive in 2024. Finally, green represents profiles that are still active in 2024. Strikingly, there is a higher number of active profiles, both during the term and in 2024, for PT (Partido dos Trabalhadores) and PSOL (Partido Socialismo e Liberdade), both being center left, or leftist, parties. Another interesting result is the number of active profiles for PSB (Partido Socialista Brasileiro), a centrist party: out of 12 candidates, 10 are still active to this day. Candidates affiliated with the party of former president Jair Bolsonaro, PSL (Partido Social Liberal), only had 4 accounts that are still active out of 12, and 5 were never active during the period studied. Thus, we have a strong ideological component to explain which candidates are active on Twitter. It seems more left leaning parties have a more keen interest in using this platform to campaign. Figure 5 shows the same results but using the current (2024) party of the candidates.

Figure 5. Profile activity on the 10 parties with more candidates (Party 2024)



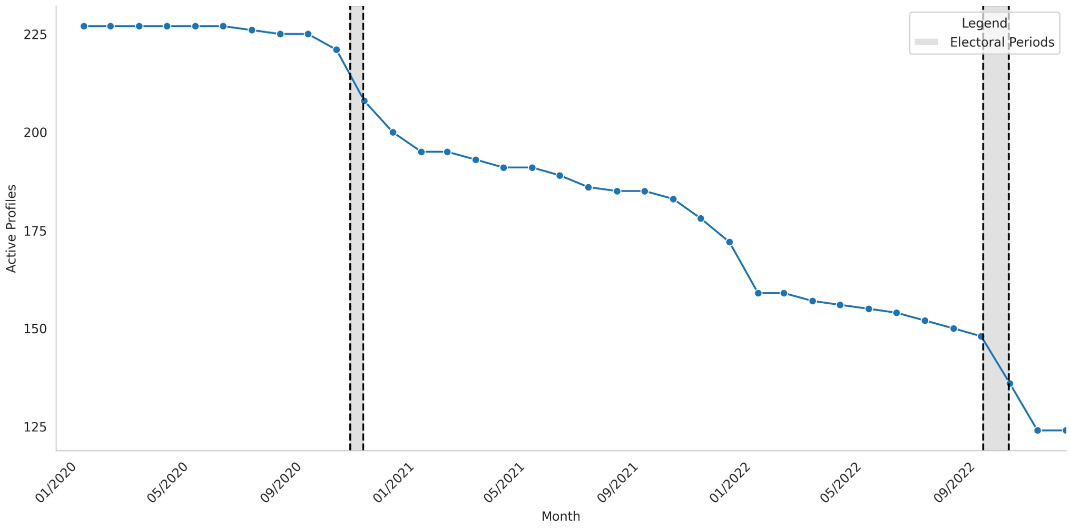
There are two striking changes here: There are a lot of transition between parties on the sample we analyze, and most of the candidates that were scattered between other parties to run for mayor in 2020 converged to UNIÃO (UNIÃO BRASIL) and PL (Partido Liberal), the latter being the current party of the former president Jair Bolsonaro. Now, the (center-)leftist parties are no longer the majority in active profiles, and we have that 19 out of 26 politicians of PL are still active in 2024 on Twitter. UNIÃO, a center-right party, has 15 profiles active out of 25. In conclusion, even if the previous figure showed a skew of left leaning profiles on our sample, we have an even distribution along the ideology axis on our sample. Now, we turn to explore the activity, in terms of volume of publications, of these politicians on Twitter. Figure 7 shows the monthly total number of publications made by the profiles of the candidates during the 2020 to 2022 period.

Figure 6. Total Volume of publications in 2020 to 2022



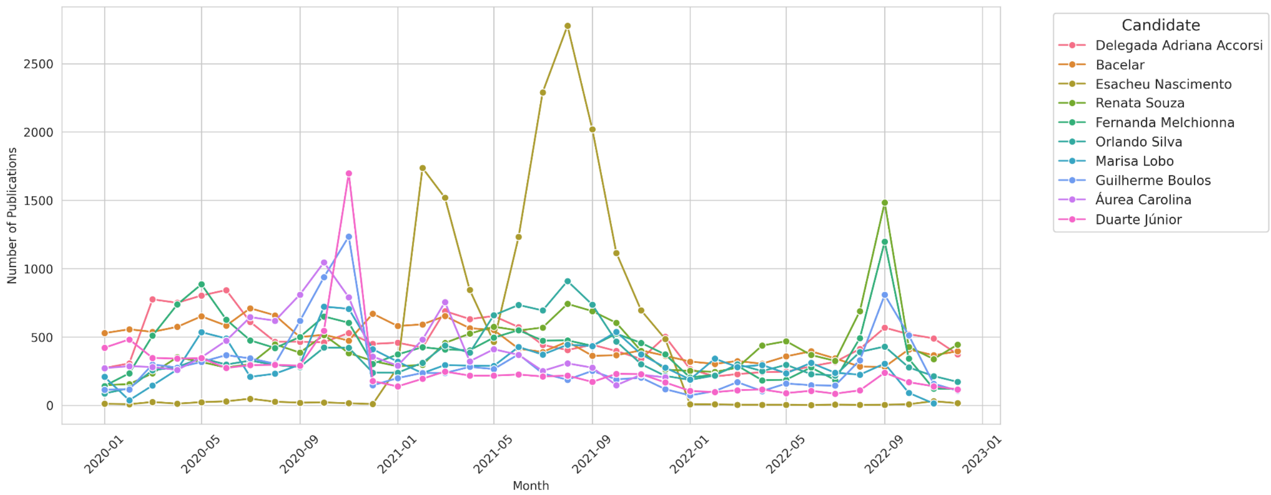
There's two main patterns that can be observed in this series: First, there is a clear shock during the electoral periods, causing an increase in the number of publications in the months preceding the elections. We can see that this pattern is true in the municipal elections (November, 2020) and in the general elections (September, 2022), even if the latter has a smaller impact. Second, we can see that the average number of publications in 2020, the first year of the COVID-19 pandemic, is higher than the other two years, and there is a steady decrease over the three year period, with 2022 showing the lowest average. This could be explained by the fact that the restrictions regarding movement and social contact were loosened, allowing these politicians to gradually return to more traditional methods of political communication. Moreover, after losing the elections, politicians may feel less inclined to make frequent use of social media.

Figure 7. Active profiles during 2020-2022 (Monthly).



As figure 8 shows, even though elections may have an impact on this, the decline on activity[6] is gradual. In 2020, the loss of profiles is minimal, with only a handful of candidates quitting Twitter. However, after the 2020 elections, there is a gradual decline in the number of active profiles. By the end of 2022, only a little more than half of the initial profiles remained active. Figure 9 shows the distribution of publications made by the 10 profiles with more publications total.

Figure 8. Top 10 Profiles with more publications overall.



[6] As measured by month of last publication on *Twitter/X*.

IV. Key Vaccine and Vaccine-Related Events

Since the onset of the COVID-19 emergency, several key events have occurred worldwide and in Brazil. We tracked these events for each semester in 2020, 2021, and 2022. The events that were mapped and grouped into categories. The purpose of this investigation was to better understand the context of the pandemic, what was happening at that specific time and what may have affected the mayoral candidate´s tweets.

We identified dates that refer to: a) events related to vaccination from the beginning of clinical trials to the advances in vaccination, and b) COVID-19-related political events.

The vaccination events refer to:

a. Clinical Trials;
b. Clinical trial interruption due to the investigation of an adverse effect;
c. Vaccine procurement;
d. Vaccine Approval by regulatory authorities;
e. Criticism/Denialism regarding the safety and/or effectiveness of the vaccine;
f. Defense of alternative vaccine treatment;
g. Start of vaccination;
h. Interruption of vaccination due to the investigation or confirmation of adverse effects for certain individuals or groups;
i. Approval and start of application of vaccine doses
j. Approval and initiation of childhood vaccination
k. Criticism/Denialism regarding the safety and/or efficacy of childhood vaccines

The political events, refer to:

a. President Bolsonaro´s speeches and positioning
b. Demonstration by Bolsonaro´s allies
c. "Carta" from state governors demanding vaccination
d. Changes of Health Ministers
e. CPI that investigated COVID-19 events about purchase of vaccine by the Federal Government and his allies

f. Elections

The short timeline in the table below reports the main events for Brazil and the rest of the world.

Table 11. Main Events related to the COVID-19 pandemic (2020-2022)

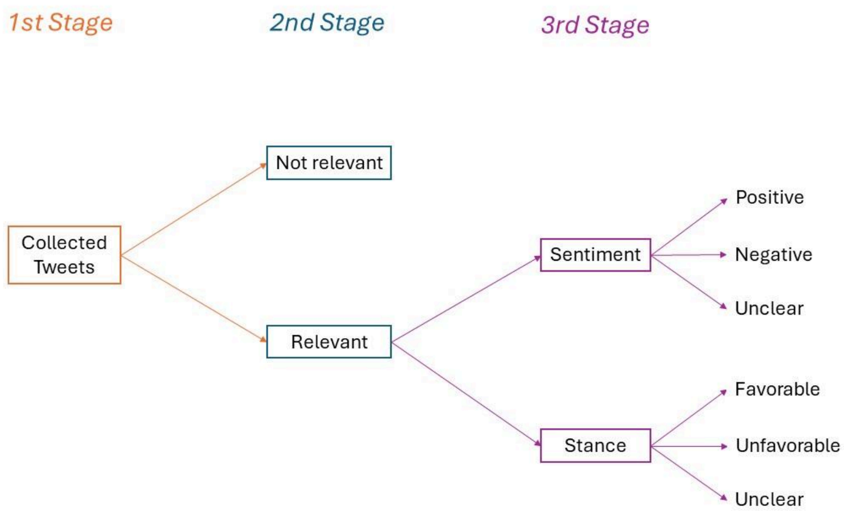
Event	Date	Vaccine-Related	Politics-Related	Children-Related
Health emergency due to COVID-19	March/2020	-	-	-
Announcement of first vaccine teste in USA	March/2020	Yes	-	-
Bolsonaro dismisses Henrique Mandetta and Teich announced as new health minister of Brazil	April/2020	-	Yes	-
Nelson Teich leaves his position as minister and Pazuello takes over as interim	May/2020	-	Yes	-
Agreement between Butantan and Sinovac	June/2020	Yes	-	-
Agreement between Astrazeneca, Fiocruz and Ministry of Health	June/2020	Yes	-	-
Start of the municipal election campaign	September/2020	-	Yes	-
Brazilian Municipal Elections	November/2020	-	Yes	-
Beginning of USA vaccination	December/2020	Yes	-	-
Brazilian Federal Government decides to buy CoronaVac	December/2020	Yes	-	-
Anvisa approved Coronavac and Astrazeneca for emergency use	January/2021	Yes	-	-
Adults (according to NPI criteria) begin COVD-19 vaccinations	January/2021	Yes	-	-
Governors ask Bolsonaro to activate WHO to speed up vaccines	March/2021	Yes	-	-
Marcela Queiroga announced as new Minister of Health	March/2021	-	Yes	-
Anvisa approves Janssen for emergency use approval	March/2021	Yes	-	-
Pandemic CPI to investigate delays in purchasing Pfizer vaccines	April/2021	-	Yes	-
Anvisa authorizes Pfizer vaccine for children over 12 years old	June/2021	Yes	-	Yes

Government recommends vaccination against COVID-19 in pregnant and postpartum women without comorbidities	July/2021	Yes	-	Yes
Start of the first booster dose application for adults	September/2021	Yes	-	-
Pandemic CPI approves final report that calls for 80 indictments	October/2021	-	Yes	-
Ministry of Health includes children aged 5 to 11 in the vaccination campaign against COVID-19	January/2022	Yes	-	Yes
Approved expansion of CoronaVac use for children and adolescents aged 6 to 17	January/2022	Yes	-	Yes
Start of the second booster dose application for adults	March/2022	Yes	-	-
Pfizer announces vaccines against COVID-19 adapted to Ômicron	June/2022	Yes	-	-
Anvisa approves emergency use of CoronaVac for children aged 3 to 5	July/2022	Yes	-	Yes
Beginning of the national election campaign	August/2022	-	Yes	-
Anvisa approves Pfizer vaccine against COVID-19 for children aged 6 months to 4 years	September/2022	Yes	-	Yes
Presidential and Gubernatorial Elections	October/2022	-	Yes	-
Anvisa approves bivalent Pfizer vaccines for booster dose against COVID-19	November/2022	Yes	-	-
Anvisa approves Pfizer vaccines for booster dose against COVID-19 for children and adolescents	Dezembro/2022	Yes	-	Yes

V. Tweet Classification Process

The categorization of tweets from candidates for mayor in the Brazilian capitals took place in three distinct stages. The first stage consisted of the extraction of tweets for each user based on keywords. The second stage involved the classification of tweets as relevant or not relevant. In the third stage, tweets classified as relevant to the study were further annotated by stance and sentiment type. The tasks in stages 2 and 3 were done contemporaneously by two different groups of coders. Additionally, the coders registered the tweets that mentioned the vaccination of children and adolescents. Figure 2 illustrates all adopted stages mentioned above.

Figure 9. Stages of the Tweet Classification Process



V. I. Sample Selection

The tweets were collected in two distinct phases: For 2020 and 2021, we used the X/Twitter API, extracting the publications directly from Twitter using the profile usernames collected on the previous steps. However, for 2022, the tweets had to be collected using a different protocol. For this year, we used twscrape,[7] a dedicated scraper that allows us to gather most of the publications with minimal loss. Each line in our dataset represents a unique Tweet by a specific candidate on a given date. For each tweet, we collected the link/URL, content (including images, videos, and links), date and time, and the number of likes, retweets, and quoted tweets associated with each post. Only the text was maintained in the annotation. Both original messages and retweets are in the dataset.

For data collection, we defined keywords by the following topics: vaccines and vaccination, COVID-19 vaccines and laboratories, geography, demography, adverse and side effects, alternative treatments, and additional terms. We adopted alternative spelling to

[7] Available at https://github.com/vladkens/twscrape.

capture possible spelling mistakes. For each term, we considered both the upper and lower case.[8]

Additionally, after the manual classification of the entire sample, additional terms were added to the list of keywords, due to the recognition of their relevance in the debate associated with COVID-19 vaccination. The additional terms included words such as, *'DoriaVac'*; *Cobaia*; *Jacaré*; *Jacare*; '*Ditadória'*; 'Ditadoria'; *Va-china*; '*Vachinação'*; and '*Va-chinacao'.*

For these additional terms, most were observed in tweets with negative stances about COVID-19 vaccines and posted by five candidates - Alexander Brasil (PRTB); Capitão Assumção (PATRIOTA); Cezar Leite (PRTB); Fred Luz (NOVO); Marisa Lobo (AVANTE). These terms include: '*DoriaVac'* and '*Va-china,'* which are intended to associate the COVID-19 vaccine with a specific political leader or country. Moreover, terms commonly used by then President Jair Bolsonaro while mentioning or referring to vaccines and vaccination in interviews, official speeches, and social media posts (e.g., *cobaia* (guinea pig) and *jacaré[e]* (alligator)) were similarly included.

Table 12 summarizes the final keywords in Brazilian Portuguese according to the topics defined in this search strategy.

Table 12. Topics definition and the Keywords used to collect Tweets from candidates in state capitals in 2020, 2021, and 2022.

Topic	Definition	Keywords
Vaccines and Vaccination	Terms related to vaccines and/or vaccination, and mandatory vaccination	[Vv]acin; [Vv]assina; [Vv]acinacao [Vv]asina; [Ii]munização; [Ii]muniza; [Ii]munisa; [Dd]ose; [Dd]oze; [Rr]eforço; [Ii]munobiologico, [Ii]munisação;[Oo]brigatoriedade; [Oo]brigar
COVID-19 Vaccines and Laboratories	Terms related to COVID-19 vaccines, pharmaceutical industries, and laboratories.	CoronaVac - [Cc]orona[Vv]ac; [Cc]ova[Xx]in; [Cc]omuna[Vv]ac; [Ss]inovac; AstraZeneca - [Aa]stra[Zz]eneca; [Aa]stra[Zz]enica; [Oo]xford; [Oo]xfort; [Oo]xfor; [Vv]axzvria Pfizer - [Pp]fizer; [Pp]eizer; [Pp]pfaizer; [Ff]aizer; [Ff]eizer; [Bb]arat; [Bb]iontech;

[8] The original R script used in the filtering process is available upon request.

		[Bb]iontec; [Cc]omyrnaty; [Cc]omimaty; [Bb]iontech [Mm]anufacturing [Gg]mbh; Moderna - [Vv]acina da [Mm]oderna; [Vv]acina [Mm]oderna; [Ss]pikevax; [Mm]oderna [Bb]iontech; mRNA-1273; CX-024414 Sputnik - [Ss]putnik; [Ss]putinik; [Ss]putink; [Ss]putinic; [Ss]putinikV; [Gg]amaleya; [Gg]amaleia Janssen - [Jj]ansen; [Jj]anssen; [Jj]&[Jj]: [Jjohnson & [Jjohnson: [Jj]honson & [Jj]honson: [Jj]onson: [Jj] & [Jj]: [Jjohnson: [Jjjohnsons; [Jj]honson; [Jjancen; [Aa]d26.COV2S Covaxin - [Cc]ovaxin; [Cc]ovachin; [Bb]harat [Bb]iotech Novavax - [Nn]ovavax; [Cc]ovavax; [Nn]uvaxovid; NVX-CoV2373; TAK-019; SARS- CoV-2 rS with Matrix-M1 adjuvant; [Ss]erum [Ii]nstitute of [Ii]ndia; [Nn]ovavax; [Ff]ormulation Sinopharm - [Ss]inopharm; BIBP; [Ss]inofarm Other Laboratories - [Bb]utantan; [Bb]utanta; [Ff]iocruz; @fiocruz; [Ff]iocrus
Geography	Countries associated with the development and production of specific COVID-19 vaccines. This topic includes expressions associated with one or more countries.	[Vv]achina; [Vv]achinada; [Vv]achin@da; [Vv]axina; [Vv]acina da [Cc]hina; [Vv]acina [Cc]hinesa; [Vv]acina [Bb]ritânica; [Vv]acina [Cc]ubana; [Vv]acina [Rr]ussa; [Vv]acina da [Rr]ussia
Adverse and Side Effects*	Terms associated with adverse or side effects from vaccines, including words associated with COVID-19 vaccines and other vaccines. We included words related to vaccines regardless of the absence or presence of scientific evidence of association.	[Ee]efeito [Cc]olateral; [Ee]feito [Aa]verso; [Cc]hoque [Aa]nafilático; [Aa]nafilaxia; [Ss][índrome de [Gg]uillain-[Bb]arré (SGB); [Mm]iocardite; [Ii] inflamação do coração; [Pp]eriocardite; [Tt]rombose; [Tt]rombocitopenia; [Tt]erapia [Gg]ênica; [Tt]erapia [Gg]enética; [Aa]taque de [Cc]oração; [Aa]utismo; [Pp]aralisia; [Cc]onvulsões; [Dd]erramе; AVC; [Ss]índrome Inflamatória Multissistêmica; [Ss]índrome de Kawasaki; [Dd]or no [Cc]oração; [Dd]or no [Pp]eito; [Óo]bito; [Aa]menoreia; [Rr]eação [Aa]lérgica; [Pp]arada [Cc]ardíaca; [Ll]esões [Gg]raves;[Cc]omorbidades; [Cc]âncer; [Mm]ortalidade; [Mm]orte [Ss]úbita; [Mm]al

		[Ss]úbito; [Aa]borto; [Cc]oagulação; [Ii]nfarto; [Rr]eação [Aa]deversa; [Dd]oença [Aa]utoimune; [Cc]olateral; [Ee]feito [Cc]olateral
Other Vaccines, COVID-19 related Medications and Therapeutics	Terms associated with treatments of COVID-19 patients. This list includes medication names and therapies proposed during the COVID-19 pandemic in Brazil. The list was composed regardless of the presence or absence of scientific evidence of the efficacy of these medications and treatments.	[Tt]ratamento precoce; [Tt]ratamento precosse; [Tt]ratamento preventivo; [Cc]loroquina; [Hh]idroxicloroquina; [Hh]idroxocloroquina; [Hh]idrosicloroquina; [Hh]idrocicloroquina; [Ii]droxicloroquina; [Cc]loroquinha; [Ss]pray nasal; [Ss]pray nazal; [Ii]vermectina; [Ii]nvermectina; [Oo]zonioterapia; [Oo]zônio; [Pp]roxalutamida; [Nn]itazoxanida; [Aa]nnita; [Aa]nita; [Aa]zitromicina; [Zz]inco; [Vv]itamina D; [Vv]it D; [Aa]nticorpos monoclonais; [Pp]lasma de convalescentes; [Vv]acina contra sarampo; [Vv]acina contra BCG; [Aa]nticorpo monoclonal; [Ii]nfusão de anticorpos; [Ss]otrovimabe; [Cc]asirimabe; [Ii]mdevimabe; [Pp]lasma; [Pp]lazma; [Pp]axlovid; [Nn]irmatrelvir; [Rr]itonavir; [Rr]eposicionamento de drogas; [Rr]emdesivir; [Vv]ermífugo; [Vv]ermifugo; [Dd]rogas antiandrogênicas; HCQ; NTZ; [Kk]it covid; [Kk]it-covid; [Dd]exametasona; [Dd]exametazona; [Cc]orticóide; [Cc]ortisona; [Cc]ortizona; [Bb]aricitinibe; [Rr]endesivir; [Dd]rogas de despovoamento.
Additional Terms	The terms mentioned by Bolsonaro or Bolsonaro supporters are associated with COVID-19 vaccine development, production, and possible risks and side effects. These words were identified in the speeches of Bolsonaro and Bolsonaro supporters(Lorena G. Barberia, de Paula Moreira, and Rosa, n.d.).	[Dd]oriavac; [Cc]obaia; [Jj]acaré; [Jj]acare; [Dd]itadória; [Dd]itadoria; [Vv]a-china; [Vv]achinação; [Vv]a-chinacao;

A filtered sample of tweets for 2020, 2021, and 2022 was extracted based on the specified keywords. Table 13 describes the total number of tweets and the subsample that was extracted based on the keywords.

Duplicates were removed when the same author posted identical content. The number of duplicates per tweet for each author was tracked, as some individuals frequently retweeted or reposted their content.

Table 13. Total Tweets Extracted and Sampling Frame of Tweets based on Keywords

Year	Total Tweets	Tweets Selected based on Keywords Corpus	Final Corpus Sample (after removing duplicates)	Size of Randomly Selected Tweets for Training Data Set	Size of Relevant COVID-19 Tweets for BERT Classification and 2nd Stage Correction
2020	232,014	6,115	6,048	3,002	3,046
2021	174,638	21,477	21,262	3,002	18,260
2022	110,490	3,275	3,100	3,002	98
Total	517,142	30,867	30,410	9,006	21,404

V. 2. Sample Definition: Relevant COVID-19 Vaccine Tweets

Using the corpus, the coders identified posts that did not refer to COVID-19 vaccines or vaccination (even if they contained one or more of the keywords). Emojis, images, or hyperlinks were not considered during the annotation and were not used as a justification for qualifying a tweet as relevant, having a stance for vaccines, or containing a sentiment.

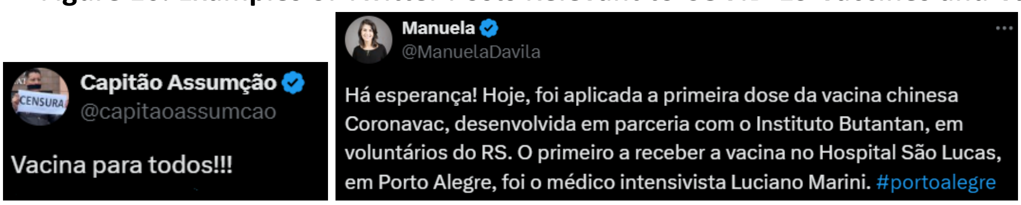
Posts in which the contents referred to COVID-19 vaccines and vaccination received a score of 1, while posts that only contained keywords, but did not address COVID-19 vaccines and vaccination received a score of 0.

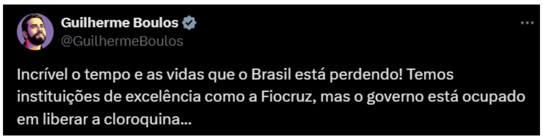
Posts that were classified as **relevant** included:

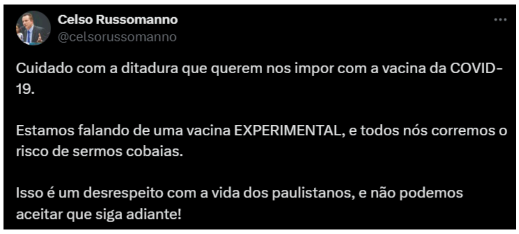
a. Direct citation of COVID-19 vaccines/vaccination;

b. Indirect reference to COVID-19 vaccines and vaccination (e.g., discussion of other vaccines and/or vaccination campaigns);
c. Terms that are specific, or can be inferred as, to COVID-19 vaccines, such as “second and third doses/shots”, “booster doses”;
d. Considering the time frame of this study, tweets that refer to vaccines and/or vaccination in Brazil or other countries even if not specific to COVID-19 specific;
e. There is mention of the vaccine-related work of institutions (e.g. Fiocruz, Butantan), scientists (e.g. Peter Hoetz), or politicians or actions and pro-vaccine or anti-vaccine (e.g. Osmar Terra, CPICOVID19) opinions or behaviors are being discussed, even in hashtags (#);
f. There is mention of the vaccine-related work of laboratories, industries or organization responsable for vaccines production or development, such as Fiocruz, Butantan, Covaxin, AstraZeneca, Oxford, etc;
g. Vaccination campaigns and public service announcements mentioning specific and quite limited age groups (e.g., “Vaccination for those 37-39 starts tomorrow”) because age-targeted announcements were almost entirely for COVID-19 vaccination campaigns;
h. Messages that discuss therapies and treatments for treating COVID-19 infection within the context of COVID-19;
i. Mentions to immunization, produced by vaccines or by contamination with COVID-19 virus (e. g. natural immunization; herd immunization, etc.); or,
j. Tweets that include terms such as “denialist (*negacionista*)”, “denialism (*negacionismo*)”, and equivalents, that directly or indirectly refers to political elite positions about vaccines.

Figure 10. Examples of Twitter Posts Relevant to COVID-19 Vaccines and Vaccination



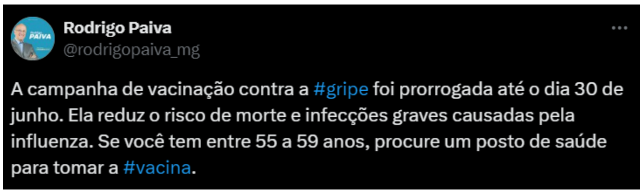


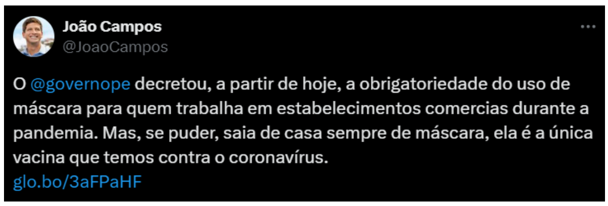


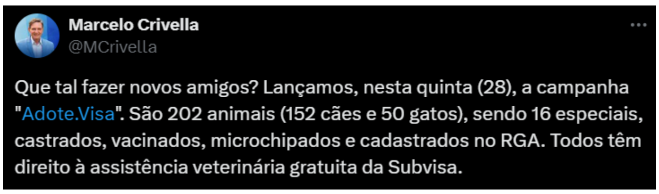
Posts that were deemed as **not relevant** include messages referring to:

a. Vaccination in animals;
b. Vaccines as a metaphor to refer to another topic (e.g. transparency as a vaccine against corruption); or
c. A message on another subject matter, but with a COVID-19 vaccine hashtag;
d. There is no mention of vaccination, vaccines, laboratories or any word presented above as relevant;
e. Messages in a foreign language that would otherwise be relevant were they in Portuguese; or,
f. Messages that discuss therapies and treatments used for treating COVID-19 infection, but where the context is not related to COVID-19.

Figure 11. Examples of Twitter Posts Not Relevant to COVID-19 Vaccines and Vaccination







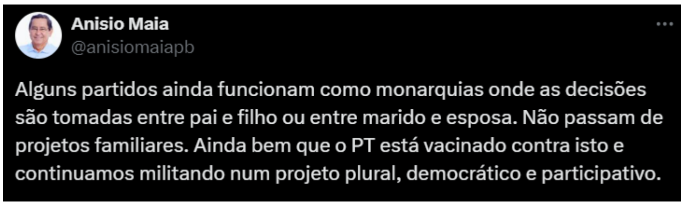


Table 14 presents the candidates who actively tweeted about the COVID-19 vaccines and vaccination in 2020 and 2021, as well as those who did not, that is, those who posted tweets classified or not as relevant to the objectives of this study. Table 15 presents the name of the candidates that posted about Covid-19 vaccines in 2020 and 2021, highlighting those that posted in one year but not the other. Finally, Figure 3 shows the total number of candidates posting about Covid-19 vaccines and vaccination in each year by state.

Table 14. Candidates and Parties with active Twitter accounts conditional on whether they published posts relevant to COVID-19 vaccines and vaccination in 2020 and 2021

State	Capital	Candidates who published relevant tweets about Covid-19 vaccines/vaccination	Candidates who have not published relevant tweets about Covid-19 vaccines/vaccination
AC	Rio Branco	Daniel Queiroz (PT)	Minoru Kinpara (PSDB) Roberto Duarte (MDB) Sebastião Bocalom (PP) Socorro Neri (PSB)
AL	Maceió	João Henrique Caldas (PSB) Lenilda Luna (UP) Maria Valéria Correia (PSOL)	Alfredo Gaspar (MDB) Cícero Filho (PC do B) Corintho Campelo (PMN) Davi Davino (PP)
AM	Manaus	Amazonino Mendes (PODE) Alberto Neto (REPUBLICANOS) David Almeida (AVANTE) Elson Marcelo Lima (PC do B) José Ricardo Wendling (PT) Romero Reis (NOVO)	Alfredo Menezes (PATRIOTA) Marco Antônio da Costa (DC) Ricardo Nicolau (PSD)
AP	Macapá	Antônio Paulo Furlan (CIDADANIA) Gianfranco Gusmão (PSTU) José Samuel Alcolumbre (DEM) Patrícia Ferraz (PODE)	Haroldo Iram (PTC) Paulo Lemos (PSOL)
BA	Salvador	Bruno Reis (DEM) Celso Coelho (PROS) Cézar Leite (PRTB) Denice Santiago (PT) Hilton Coelho (PSOL)	-

		João Carlos Bacelar (PODE) Olívia Santana (PC do B) Rodrigo Pereira (PCO)	
CE	Fortaleza	Anízio Santos (PC do B) Célio Studart (PV) Heitor Férrer (SOLIDARIEDADE) Heitor Freire (PSL) José Sarto (PDT) Luizianne Lins (PT) Paula Colares (UP) Renato Roseno (PSOL)	Wagner Gomes (PROS)
ES	Vitória	João Coser (PT) Lucínio Castelo (PATRIOTA) Nylton Rodrigues (NOVO) Sérgio Sá (PSB)	Fabrício Aquino (CIDADANIA) Edmar Lorencini (PSD) Neuza de Oliveira (PSDB)
GO	Goiânia	Adriana Accorsi (PT) Elias Vaz (PSB) Fábio Júnior (UP) Hemanuelle Jacob (PSOL) Júnio Araújo (PSL) Talles Barreto (PSDB) Vanderlan Cardoso (PSD)	Alysson Lima (SOLIDARIEDADE) Luiz Vilela (MDB) Samuel Almeida (PROS) Virmondes Cruvinel (CIDADANIA)
MA	São Luís	Eduardo Braide (PODE) Franklin Ferreira (PSOL) Hildelis Duarte (REPUBLICANOS) Rubens Júnior (PC do B) Sílvio Antônio (PRTB) Ubirajara Sousa (PSB) Yglésio Moysés (PROS)	Hertz Dias (PSTU) Jeisael de Jesus (REDE) José Evangelista (DEM)
MG	Belo Horizonte	Áurea Carolina (PSOL) Bruno Engler (PRTB) João Vitor Xavier (CIDADANIA) Lafayette Andrada (REPUBLICANOS) Luísa Barreto (PSDB) Nilmário Miranda (PT) Rodrigo Paiva (NOVO) Wadson Ribeiro (PC do B) Wanderson Rocha (PSTU) Wendel Mesquita (SOLIDARIEDADE)	Alexandre Kalil (PSD) Edmar Xavier (PMB) Marcelo de Souza (PATRIOTA) Marília Domingues (PCO)
MS	Campo Grande	Dagoberto Nogueira (PDT) Esacheu Nascimento (PP) Guto Scarpanti (NOVO) João Catan (PL) Pedro Kemp (PT) Vinícius Siqueira (PSL)	Marcelo Bluma (PV) Márcio Fernandes (MDB) Marcos Trad (PSD) Paulo Matos (PSC)
MT	Cuiabá	Emanuel Pinheiro (MDB)	Aécio Rodrigues (PSL) Gilberto Lopes (PSOL)

			Paulo Grando (NOVO)
PA	Belém	Edmilson Rodrigues (PSOL) Gustavo Sefer (PSD) Thiago Araújo (CIDADANIA) Wagner Martins (REPUBLICANOS)	Cássio Andrade (PSB) Everaldo Eguchi (PATRIOTA) José Priante (MDB)
PB	João Pessoa	Anísio Maia (PT) Cícero Lucena (PP) Ítalo Guedes (PSOL) Ruy Carneiro (PSDB) Wallber Virgolino (PATRIOTA)	Camilo Duarte (PCO) Edilma Freire (PV) Nilvan Ferreira (MDB) Raoni Mendes (DEM) Ricardo Coutinho (PSB)
PE	Recife	Alberto Feitosa (PSC) João Campos (PSB) Marília Arraes (PT)	José Filho (DEM)
PI	Teresina	Fábio Novo (PT) Fábio Sérvio (PROS)	Diego Melo (PATRIOTA) Fábio Abreu (PL) Gervásio Santos (PSTU) Gessy Fonseca (PSC) José Pessoa (MDB) Kleber Montezuma (PSDB) Lucineide Barros (PSOL)
PR	Curitiba	Camila Lanes (PC do B) Christiane Yared (PL) Fernando Francischini (PSL) João Arruda (MDB) João Moraes (NOVO) Jorge Brand (PDT) José Boni (PTC) Marisa Lobo (AVANTE) Paulo Opuszka (PT) Rafael Greca (DEM)	Eloy Casagrande (REDE) Renato Mocellin (PV)
RJ	Rio de Janeiro	Benedita da Silva (PT) Clarissa Garotinho (PROS) Cyro Garcia (PSTU) Eduardo Paes (DEM) Frederico Luz (NOVO) Glória Silva (PSC) Luiz Lima (PSL) Marcelo Crivella (REPUBLICANOS) Martha Rocha (PDT) Paulo Messina (MDB) Renata Souza (PSOL)	Suêd Haidar (PMB)
RN	Natal	Carlos Medeiros (PV) Jaidy Oliveira (DC) Jean Prates (PT) Rosália Fernandes (PSTU)	Álvaro Dias (PSDB) André Azevedo (PSC) Hélio Oliveira (PRTB) Hermano Moraes (PSB) Kelps Lima (SOLIDARIEDADE) Maria Valentim (PSOL) Sérgio Leocádio (PSL)

RO	Porto Velho	Hildon Chaves (PSDB) Ramon Cujui (PT) Vinícius Miguel (CIDADANIA)	Breno Mendes (AVANTE) Eyder do Carmo (PSL) João Bertolin (PTB)
RR	Boa Vista	Antônio Nicoletti (PSL) Gerlane Baccarin (PP) Linoberg Almeida (REDE) Shéridan Oliveira (PSDB)	Arthur Machado (MDB) Fábio Almeida (PSOL) Luciano Castro (PL) Otaci do Nascimento (SOLIDARIEDADE)
RS	Porto Alegre	Fernanda Melchionna (PSOL) Gustavo Paim (PP) João Derly (REPUBLICANOS) Juliana Brizola (PDT) Manuel d'Ávila (PC do B) Montserrat Martins (PV) Nelson Marchezan Júnior (PSDB) Sebastião Melo (MDB) Valter Nagelstein (PSD)	Júlio Flores (PSTU)
SC	Florianópolis	Alexander Brasil (PRTB) Ângela Amin (PP) Elson Pereira (PSOL) Gean Loureiro (DEM) Orlando Neto (NOVO)	Gabriela Santetti (PSTU) Pedro Silvestre (PL)
SE	Aracaju	Alexis Pedrão (PSOL) Edvaldo Filho (PDT) Márcio Macedo (PT) Rodrigo Valadares (PTB)	Danielle Soares (CIDADANIA) Georlize Teles (DEM) Juraci Nunes (PMB) Paulo Cruz (DC)
SP	São Paulo	Ângelo Matarazzo (PSD) Arthur do Val (PATRIOTA) Celso Russomanno (REPUBLICANOS) Guilherme Boulos (PSOL) Jilmar Tatto (PT) Joice Hasselmann (PSL) Márcio França (PSB) Marina Helou (REDE) Orlando Silva (PC do B) Vera Lúcia Salgado (PSTU)	Levy Fidelix (PRTB)
TO	Palmas	Alan Barbiero (PODE) Cínthia Ribeiro (PSDB) Tiago Andrino (PSB) Vanda Monteiro (PSL)	Gil Barison (REPUBLICANOS) João Bazzoli (PSOL) José Júnior (PROS) Marcelo Lelis (PV)

Table 15. Candidates and Parties with active Twitter accounts conditional on whether they published posts relevant to COVID-19 vaccines and vaccination in 2020* and 2021**

State	Candidates that published about vaccines in 2020	Candidates that published about vaccines in 2021

AC	Daniel Zen	Daniel Zen, Roberto Duarte**, Tião Bocalom**
AL	Jhc, Lenilda Luna, Valeria Correia	Lenilda Luna, Jhc, Valeria Correia, Alfredo Gaspar De Mendonça**
AM	Amazonino Mendes, Capitão Alberto Neto, David Almeida*, Marcelo Amil, Romero Reis, Ze Ricardo	Marcelo Amil, Chico Preto**, Ze Ricardo, Capitão Alberto Neto, Amazonino Mendes, Romero Reis, Coronel Menezes**
AP	Dr Furlan, Gianfranco, Josiel, Patrícia Ferraz	Dr Furlan, Paulo Lemos**, Josiel, Patrícia Ferraz, Gianfranco
BA	Bacelar, Bruno Reis, Celsinho Cotrim*, Cezar Leite, Hilton Coelho, Major Denice*, Olivia, Rodrigo Pereira	Bacelar, Hilton Coelho, Bruno Reis, Olivia, Cezar Leite, Rodrigo Pereira
CE	Anizio, Celio Studart, Heitor Férrer, Heitor Freire, Luizianne Lins, Paula Colares*, Renato Roseno, Sarto	Sarto, Heitor Freire, Luizianne Lins, Capitão Wagner**, Renato Roseno, Heitor Férrer, Celio Studart, Anizio
ES	Capitão Assumção, Coronel Nylton*, Joao Coser, Sergio Sá*	Capitão Assumção, Mazinho**, Joao Coser
GO	Delegada Adriana Accorsi, Elias Vaz, Fábio Junior, Major Araújo, Manu Jacob, Talles Barreto, Vanderlan Cardoso	Fábio Junior, Vanderlan Cardoso, Alysson Lima**, Elias Vaz, Virmondes Cruvinel**, Delegada Adriana Accorsi, Talles Barreto, Major Araújo, Manu Jacob

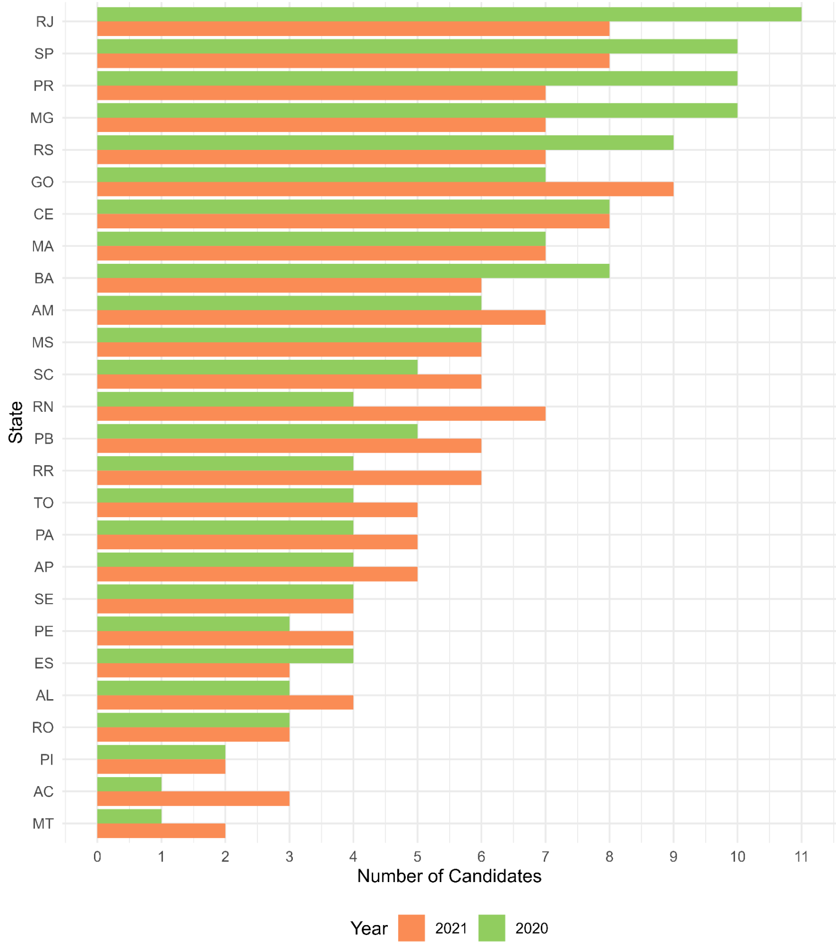
MA	Bira, Duarte, Eduardo Braide, Professor Franklin, Rubens Junior, Silvio Antonio*, Yglésio Moyses	Eduardo Braide, Rubens Junior, Bira, Jeisael**, Yglésio Moyses, Duarte, Professor Franklin
MG	Áurea Carolina, Bruno Engler, João Vitor Xavier, Lafayette Andrada*, Luisa Barreto, Nilmário Miranda*, Professor Wendel Mesquita*, Rodrigo Paiva*, Wadson Ribeiro*, Wanderson Rocha	Áurea Carolina, Bruno Engler, João Vitor Xavier, Wanderson Rocha, Marilia Domingues**, Kalil**, Luisa Barreto
MS	Dagoberto*, Esacheu Nascimento, Guto Scarpanti, João Henrique, Pedro Kemp*, Vinicius Siqueira	Marquinhos Trad**, Marcio Fernandes**, Guto Scarpanti, Esacheu Nascimento, Vinicius Siqueira, João Henrique
MT	Emanuel Pinheiro	Emanuel Pinheiro, Gilberto Lopes Filho**
PA	Edmilson Rodrigues, Gustavo Sefer, Thiago Araujo, Vavá Martins*	Edmilson Rodrigues, Thiago Araujo, Delegado Federal Eguchi**, Priante**, Gustavo Sefer
PB	Anísio Maia, Cicero Lucena, Italo Guedes, Ruy Carneiro, Wallber Virgolino	Ruy Carneiro, Wallber Virgolino, Cicero Lucena, Anísio Maia, Ricardo Coutinho**, Italo Guedes
PE	Coronel Feitosa, João Campos, Marilia Arraes	João Campos, Marilia Arraes, Coronel Feitosa, Mendonça Filho**
PI	Fabio Novo, Fábio Sérvio*	Fabio Novo, Mario Rogerio**
PR	Camila Lanes, Christiane Yared*, Dr João Guilherme Do Novo, Fernando Francischini,	Goura, Fernando Francischini, Rafael Greca, Camila Lanes,

	Goura, João Arruda, Marisa Lobo, Paulo Opuszka*, Rafael Greca, Zé Boni*	Marisa Lobo, João Arruda, Dr João Guilherme Do Novo
RJ	Benedita Da Silva, Clarissa Garotinho, Crivella*, Cyro Garcia, Delegada Martha Rocha, Eduardo Paes, Fred Luz*, Glória Heloiza*, Luiz Lima, Paulo Messina, Renata Souza	Benedita Da Silva, Renata Souza, Eduardo Paes, Delegada Martha Rocha, Clarissa Garotinho, Luiz Lima, Paulo Messina, Cyro Garcia
RN	Carlos Alberto (Beto), Jaidy Oliver*, Rosália Fernandes, Senador Jean	Senador Jean, Alvaro Dias**, Carlos Alberto (Beto), Coronel Azevedo**, Rosália Fernandes, Hermano Morais**, Kelps Lima**
RO	Hildon Chaves, Ramon Cujui, Vinicius Miguel	Ramon Cujui, Hildon Chaves, Vinicius Miguel
RR	Gerlane, Linoberg, Nicoletti*, Shéridan	Arthur Henrique**, Shéridan, Ottaci**, Fabio Almeida**, Gerlane, Linoberg
RS	Fernanda Melchionna, Gustavo Paim, João Derly, Juliana Brizola, Manuela, Montserrat Martins*, Nelson Marchezan Júnior*, Sebastião Melo, Valter	Fernanda Melchionna, Sebastião Melo, Juliana Brizola, Valter, Manuela, João Derly, Gustavo Paim
SC	Alexander Brasil, Angela Amin, Gean, Orlando, Professor Elson	Gean, Alexander Brasil, Orlando, Gabriela Santetti**, Angela Amin, Professor Elson

SE	Alexis Pedrão, Edvaldo, Márcio Macedo, Rodrigo Valadares	Edvaldo, Alexis Pedrão, Márcio Macedo, Rodrigo Valadares
SP	Andrea Matarazzo*, Arthur Do Val Mamãe Falei, Celso Russomanno*, Guilherme Boulos, Jilmar Tatto, Joice Hasselmann, Márcio França, Marina Helou, Orlando Silva, Vera	Guilherme Boulos, Jilmar Tatto, Orlando Silva, Arthur Do Val Mamãe Falei, Joice Hasselmann, Marina Helou, Márcio França, Vera
TO	Alan Barbiero*, Cinthia Ribeiro, Tiago Amastha Andrino, Vanda Monteiro	Cinthia Ribeiro, Professor Júnior Geo**, Vanda Monteiro, Tiago Amastha Andrino, Barison**

Note: Candidates that tweeted in 2020, but not 2021 are marked with * and those that tweeted in 2021, but not 2020, are marked with **.

Figure 12. Number of Candidates that Posted About Covid-19 Vaccines per State



V. 3. Classification of Stance, Sentiment and Children-Related Relevant Tweets

The written content of the posts was classified as belonging to one of three categories: (i) favorable; (ii) unfavorable; (iii) unclear towards COVID-19 vaccines and vaccination.

a. Stance

Tweets from these individual's accounts were classified as (i) "**favorable**" if they promoted COVID-19 vaccines and vaccination. These are tweets that:

a) called for the development and approval of COVID-19 vaccines;
b) emphasized the urgency and the necessity of COVID-19 vaccines;
c) defended or celebrated the vaccination of the population using one or all COVID-19 vaccines available;
d) expressed confidence in the development of COVID-19 vaccines and science;

e) celebrated clinical trials, scientific breakthroughs, and agreements between governments and laboratories (e.g. Fiocruz and Butantan) related to COVID-19 vaccine development;

f) announced significant events related to COVID-19 vaccine procurement, approvals and the beginning of immunization campaigns;

g) supported mandatory COVID-19 vaccine mandates and/or restrictions for unvaccinated;

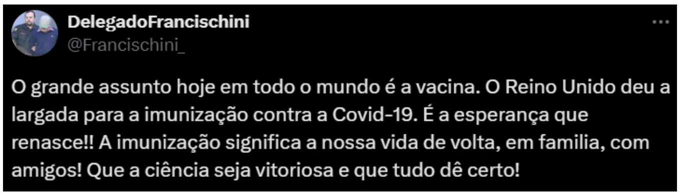
h) reported the number of COVID-19 vaccinations administered in a specified timeframe (even if not necessarily associating this text with any opinion or encouragement);

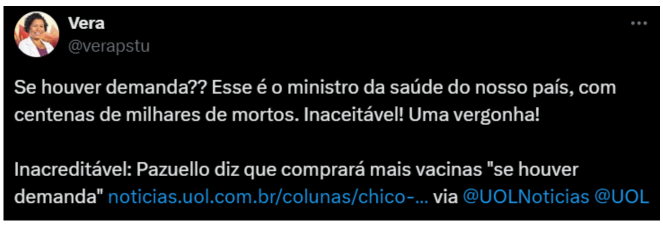
i) provided information to enhance accessibility to COVID-19 vaccines (e.g. providing information about dates, times and locations or announcing a new vaccine center, or guidelines on how the vaccination process works; or new groups that are eligible for vaccination;

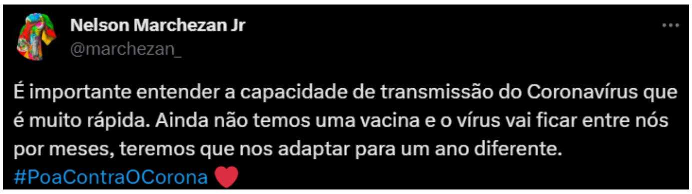
j) criticizing public or private actors for management practices and leadership that delayed procurement of COVID-19 vaccines or administration of COVID-19 vaccination; or

k) that discusses medications or therapies in addition to taking a favorable stance to vaccination (according to the other rules) explicitly.

Figure 13. Examples of Twitter Posts with Stance Favorable to COVID-19 Vaccines and Vaccination







The second category, "**unfavorable**" (ii), is composed of tweets that express unfavorable positions regarding COVID-19 vaccination and vaccines. These are tweets that:

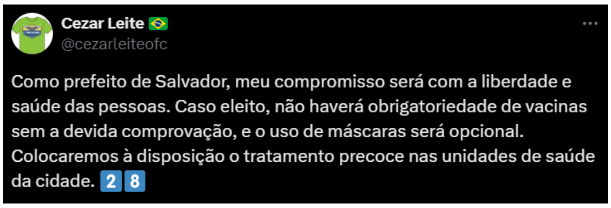
a) criticized and/or questioned the approval, procurement, and adoption of one or all COVID-19 vaccines (including clinical trials) and vaccinations campaigns, as well as the need for booster shots;
b) discouraged and/or questioned COVID-19 vaccine brands, efficacy and confidence in vaccines and/or clinical trials;
c) emphasized side effects, lack of security and/or lack of confidence in clinical trials or COVID-19 vaccine development;
d) criticized international health organizations (such as the World Health Organization - WHO), pharmaceutical companies, laboratories, national health institutions (such as the Ministry of Health, Butantan and Fiocruz), and public regulatory health agencies (such as ANVISA), along with their policies aimed at ensuring the safety and use of COVID-19 vaccines;
e) criticized and questioned the restriction of activities in the absence of mass vaccine coverage;
f) opposed mandatory COVID-19 vaccination, vaccine passports, etc;
g) raised concerns about long-term effects or unknown consequences of the COVID-19 vaccine;
h) contribute to conspiracies and controversies surrounding the ingredients used in manufacturing COVID-19 vaccines;
i) express refusal/rejection and/or reluctance to COVID-19 vaccine uptake;
j) tweets that express feelings of hesitancy, such as tweets that emphasize feelings of fear to potential side effects. Feelings of hesitancy that should be classified as "neutral" include "delay in acceptance" as per the definition of COVID-19 vaccine hesitancy by the WHO;

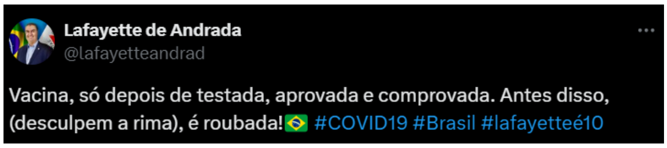
k) talk about delay in getting vaccinated, for example, mentioning that they might get the vaccine in the future upon some condition, etc.;

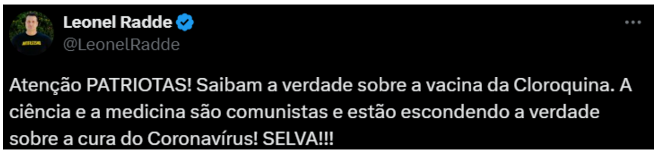
l) emphasizes low-risk from natural infection for specific individuals (e.g. children); or,

m) discusses medication or therapies in addition to taking an unfavorable stance to vaccination (according to the other rules) explicitly.

Figure 14. Examples of Twitter Posts with Stance Unfavorable to COVID-19 Vaccines and Vaccination







The third category, "**unclear,**" is a category that the coders can use to categorize tweets where there is either:

a) insufficient content to permit identifying stance, but it is clear that the author of the tweet has a stance towards COVID-19 vaccines and vaccination;

b) discussion of medications or therapies without taking an unfavorable or favorable stance to vaccination (according to the other rules) explicitly;

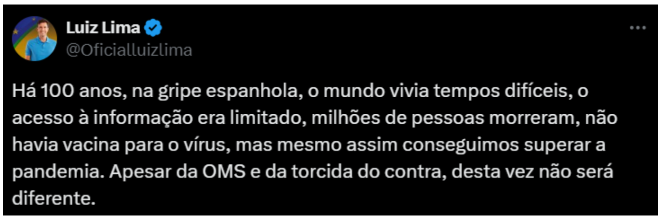
c) discussion of other vaccines (e.g., flu, polio, measles) without taking an unfavorable or favorable stance to vaccination (according to the other rules) explicitly;

d) remained ambiguous in the sense that their opinions could be interpreted as neither favorable nor unfavorable toward vaccines or vaccination;

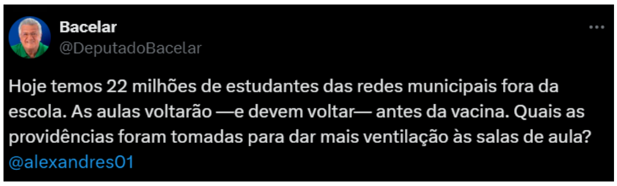
e) calls for allowing the private sector to purchase and distribute COV19- vaccines; or,

f) reported news or comments on vaccine or vaccination-related events, such as protest actions, corruption scandals (e.g., Covaxin procurement) or bad administration procedures, without expressing a specific opinion towards vaccines and vaccination.

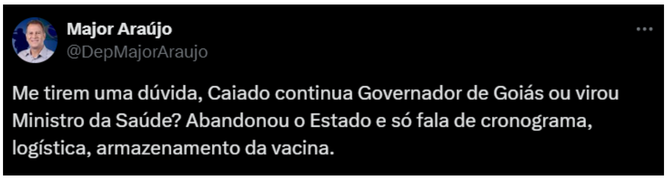
Figure 15. Examples of Twitter Posts with Stance Characterized as Unclear towards COVID-19 Vaccines and Vaccination


Luiz Lima
@Oficialluizlima

Há 100 anos, na gripe espanhola, o mundo vivia tempos difíceis, o acesso à informação era limitado, milhões de pessoas morreram, não havia vacina para o vírus, mas mesmo assim conseguimos superar a pandemia. Apesar da OMS e da torcida do contra, desta vez não será diferente.


Bacelar
@DeputadoBacelar

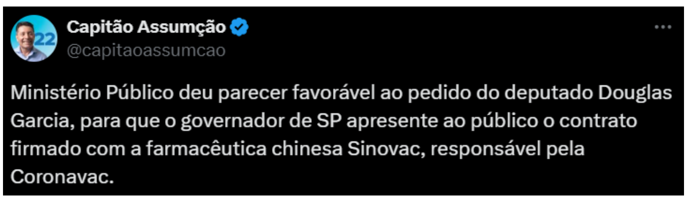
Hoje temos 22 milhões de estudantes das redes municipais fora da escola. As aulas voltarão —e devem voltar— antes da vacina. Quais as providências foram tomadas para dar mais ventilação às salas de aula? @alexandres01


Major Araújo
@DepMajorAraujo

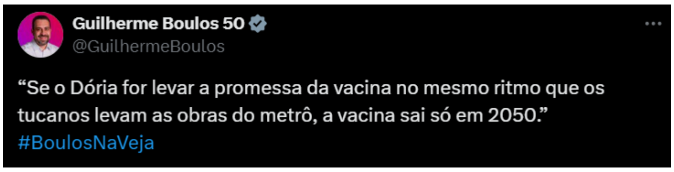
Me tirem uma dúvida, Caiado continua Governador de Goiás ou virou Ministro da Saúde? Abandonou o Estado e só fala de cronograma, logística, armazenamento da vacina.

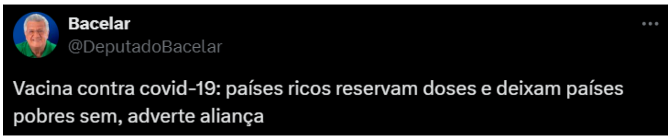
The fourth category, "**I don't know**" (iv), is a category to indicate a tweet in which the annotator is unsure about whether the annotation is favorable, unfavorable, or unclear. In this case, the tweet is reviewed considering the majority rule, and re-annotated by the senior team if the majority of annotators did not agree.

Figure 16. Examples of Twitter Posts with Stance Characterized as Unclear towards COVID-19 Vaccines and Vaccination


Capitão Assumção
@capitaoassumcao

Ministério Público deu parecer favorável ao pedido do deputado Douglas Garcia, para que o governador de SP apresente ao público o contrato firmado com a farmacêutica chinesa Sinovac, responsável pela Coronavac.





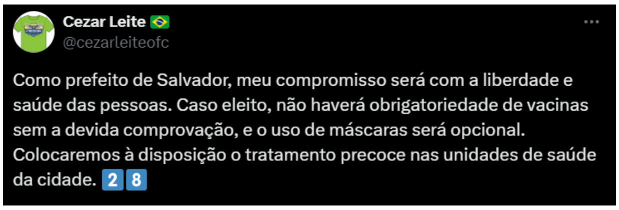
b. Sentiment

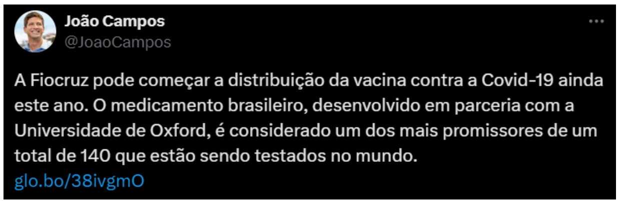
Differently from stance, sentiment was coded in relation to the overall emotions manifested in the posts, not in relation to COVID-19 vaccines. We classified the written content of the tweets as belonging to one of three categories: (i) positive; (ii) negative; (iii) unsure.

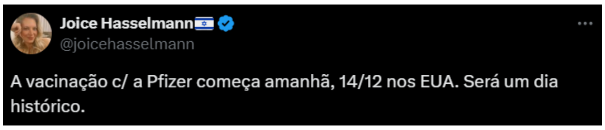
Tweets were classified as **"positive"** if the intent of the author was interpreted as transmitting positive feelings. These are posts where:

a) the tweet transmits positive emotions, for example, admiration, positive attitude, hope, fostering, progression, success, gratitude, positive emotional state (happiness, optimism, pride, etc.);
b) the state of the tweet is positive: there is an explicit or implicit clue in the text suggesting that the speaker is in a positive state, i.e., happy, admiring, relaxed, supportive, etc.;
c) tweets that express concern or reach out to individuals to ensure they get vaccines;
d) the tweet was written in an optimistic tone;
e) the tweet expresses relief;
f) the tweet provides information celebrating the number of people vaccinated, a new vaccination site or age group eligibility. These tweets are generally written in the first person singular (I) or plural (we).
g) tweets reporting the number of people vaccinated, a new vaccination site a new age group, tweets reporting information about vaccination schedule or locations

Figure 17. Examples of Twitter Posts with Sentiment Characterized as Positive



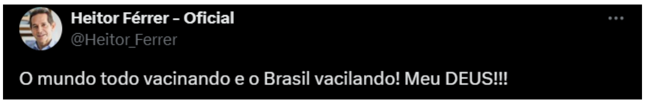


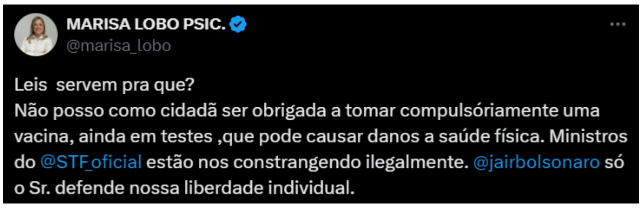


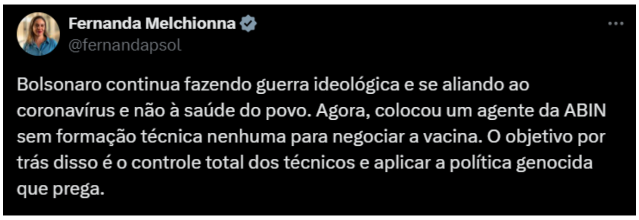
Tweets were classified as **“negative”** if the intent of the author was interpreted as transmitting mostly negative feelings. These include posts where:

a) the speaker is mostly using negative terms and language, for example, expressions of criticism, complaint, judgment, uncooperativeness, pessimism, negative emotion, fear, doubt, disappointment, anger, regret, etc.;
b) tweets that question validity/competence or highlight failures (e.g. delay in procurement or waiting for vaccines or vaccination);
c) tweets in which the need to fight refers to specific things that have not been achieved yet (e.g vaccines or benefits), or refers to general (and fundamentals) things that need to be protected (e.g life), or refers to things that the author considers unfair or wrong;
d) tweets that make references to death and dying (e.g. *homicida, mortes*, etc.)
e) tweets that emphasize scarcity or dependency and as a result vaccines are being delayed;
f) tweets that also included positives terms, but where negative messages dominated;
g) tweets that have a predominance of negative words;
h) Skepticism/tweets that share feelings of distrust; or
i) Tweets that share negative experiences.

Figure 18. Examples of Twitter Posts with Sentiment Characterized as Negative





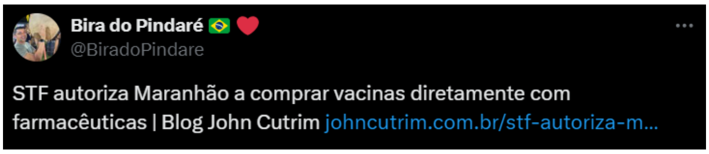


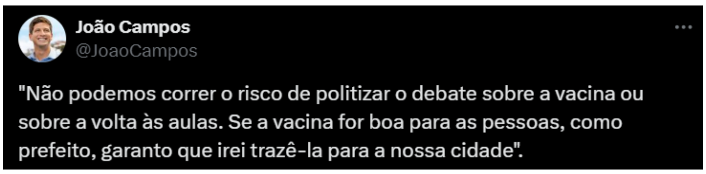
Tweets were classified as **"Unclear"** if the speaker used language where:

a) without context, it is unclear whether the content of the tweet is transmitting negative or positive emotions (e.g. sarcastic tweets where a message was sent regarding an image) or there are both positive and negative emotions. Since the image is being ignored, the tweet is classified as unclear; or,

b) tweets reporting the number of people vaccinated but without suggesting celebration for the increase in people vaccinated (e.g. "governo x vacinou 100 pessoas").

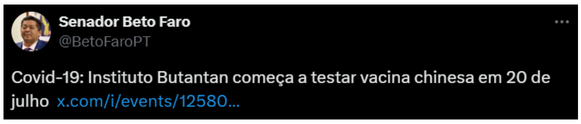
Figure 19. Examples of Twitter Posts with Sentiment Characterized as Unclear

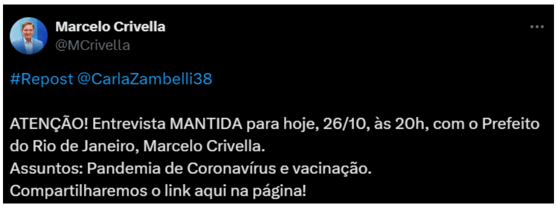




The final category was used to classify Tweets as "**I don't know.**" This category indicates a tweet in which the annotator is unsure about whether the annotation is positive, negative or unclear. In this case, the tweet is reviewed considering the majority rule, and re-annotated by the senior team if the majority of annotators did not agree.

Figure 20. Examples of Twitter Posts with Sentiment Characterized as Unsure





6c. Children and Adolescents

Each tweet was coded to identify references to children and adolescents (ages 0 to 17), pregnant women, and mentions of returning to school and school contexts provided the message also discussed COVID-19 vaccines and/or vaccination, directly or indirectly. Figure 13 shows examples of Twitter posts related to infants, children, adolescents, school-related topics, and pregnancy. These tweets include messages that:

a. discussed on-site schooling with/without vaccination of teachers, staff, and/or children;

b. addressed concerns or questions about the safety and efficacy of vaccines for children and adolescents;

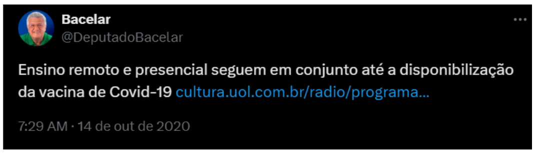
c. highlighted vaccine availability and accessibility for pregnant women, children, and adolescents;

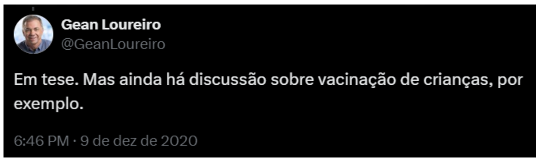
d. mentions terms specific to children vaccinations (e.g. Zé Gotinha);

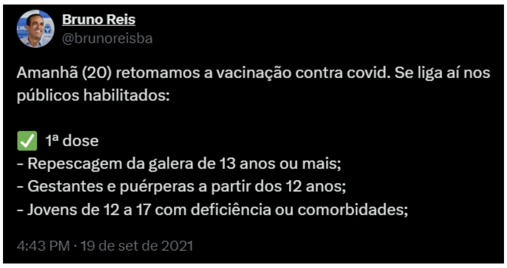
e. mention pregnant women, children or teens in discussing therapies or treatments (e.g. hidroxicloroquine in pregnant women); and/or,

f. mention to vaccine events named as “vaccine to family”, usually related to persons (or children) of all ages that lost the period to vaccination and gained another chance.

Figure 21. Examples of Twitter Posts mentioning Children and Adolescents







V.4. Classification of Confidence, Collective Responsibility, Complacency and Convenience in Children and Adolescents Sample

In the child and adolescent sub-sample of tweets, we also identified whether the tweets referred to vaccine confidence, collective responsibility, complacency and/or convenience. These categories were not mutually exclusive, and therefore most tweets were classified as belonging to more than one category.

a. Vaccination Confidence

Tweets that emphasized (i) the effectiveness and safety of vaccines, (ii) the system delivering them, including the reliability and competence of health services and professionals, and (iii) the motivations of policymakers deciding on necessary vaccines were classified as relating to confidence. Tweets emphasizing vaccine confidence included messages that discussed:

a. Safety concerns (including discussions about potential risks, such as adverse and side effects);

b. Safety concerns linked to the perceived speed at which the vaccine was created and the lack of data about its safety;

c. Discussions surrounding regulatory approval of COVID-19 vaccines by Brazilian, and/or regulatory authorities in other countries; and,

d. Discussions which emphasize the timing of vaccination of this age group (e.g., ensuring rapid or delaying vaccine administration in children or adolescents).

Figure 22. Examples of Twitter Posts mentioning Confidence in Children and Adolescents Sample

b. Vaccination Complacency

According to SAGE (2014), “vaccine complacency exists where perceived risks of vaccine-preventable diseases are low, and vaccination is not deemed a necessary preventive action.” Tweets emphasizing complacency included messages that discussed:

a. the opinion that young and healthy children already had COVID- 19, or that infection does not cause serious illness or death;

b. the efficacy or effectiveness of COVID-19 vaccines in children; and,

c. the use of alternative treatments to protect children and adoloscents including the adminstration of other vaccines (e.g. BCG and influenza).

Figure 23. Examples of Twitter Posts mentioning Complacency in Children and Adolescents Sample

c. Vaccination Collective Responsibility

In many instances, the collective benefits from greater coverage of children and adolescents against COVID-19 vaccines were emphasized with reasons highlighting that we protect others or generate population or herd immunity by vaccinating children. In our project, tweets emphasizing collective responsibility included messages that discussed:

a. the vaccination of children and adolescents to protect other vulnerable groups; and,

b. the importance of reaching higher vaccine coverage rates in children and adolescents to ensure population immunity.

Figure 24. Examples of Twitter Posts mentioning Collective Responsibility in Children and Adolescents Sample

d. Vaccination Convenience

Oftentimes, factors such as physical availability, affordability, willingness to pay, geographical accessibility, language and health literacy, and appeal of immunization services affect uptake. The quality of service, both real and perceived, and the degree to which vaccination services are delivered in a time, place, and cultural context that is convenient and comfortable also affect the decision to be vaccinated and could lead to vaccine hesitancy. tweets emphasizing convenience included messages that discussed:

a. information on the rollout of vaccination (eligibility and availability) including dates and locations where this age group could receive vaccines.

Figure 25. Examples of Twitter Posts mentioning Convenience in Children and Adolescents Sample

V.5. Review Procedure for Annotation

In the first stage, an average of 4 annotators classified tweets for relevance, children, stance, and sentiment. We followed the following rules:

1. If 75% or more of the annotators agreed on a classification category, this was the final decision to classify the specific tweet.

2. If less than 75% of the annotators agreed on the classification category, tweets with significant disagreement between coders were reviewed by a senior team of three coders and classified a second time, and a final classification was assigned to the tweet.

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