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A framework for characterising the *hows* and *whens* of social media communication during crises

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Abstract
Communication strategies are essential during crises, as they can influence people's behaviours. For governments, crises increase the need for timely communicating information and engaging with citizens. Communication is not only a matter of sharing the right content but also of understanding the communication style and how communications (should) evolve over time. We present a framework for characterising government communication patterns on social media and how such patterns influence citizen engagement based on sociological, language, and crisis theories. We study the pragmatic meaning of communications by linking it to crisis stages and uncertainty reduction goals. We instantiated the framework in a data collection of local governments communications in Argentina during COVID-19. Our findings indicate that governments reflected specific communication strategies, matching the expected crisis-related stages from the chosen theories. The proposed framework could help government officials to design, monitor, and adjust their communication strategies to achieve efficient information diffusion.

Keywords
crisis communication; e-government; social analytic; social media

1. Introduction

Crises are marked by uncertainty, severity and urgency, creating informational and emotional gaps [1]. Effective communication during crises can potentially reduce harm and save lives [2]. Modern communication technologies allow governments and citizens to collaborate in addressing crises, with social media playing a crucial role in these efforts [3]. Given the rich amount of information often disseminated in social media, they provide a timely environment for investigating crisis management patterns.

Message transmission and amplification are crucial in studying emergency communications [2]. The decision of who re-transmits a message significantly impacts its reach, as re-transmitted messages are likely to be seen by a larger audience more frequently [2]. Then, this re-transmission can be seen as a form of amplification of messages. In social media, amplification is achieved through mechanisms such as likes, comments, and retweets, all of which affect the visibility and reach of posts. These can be seen as proxies of engagement, typically mapping to three dimensions: popularity (likes), commitment (replies) and virality (shares) [4,5].

Although information propagation patterns during crises are well-documented, studies suggest that social media features can impact how users react to the content [6]. Understanding the key factors driving citizen interaction or engagement is crucial for government officials and social scientists. Research on how language influences social media engagement offers guidelines for crafting more engaging messages. In fact, the language used can reveal important cues about people's intentions and motivations.

Here, we build on sociological, linguistic, and crisis theories to examine social media engagement (in terms of popularity, commitment and virality) through the *social intents of communication*. We aim to understand *how communication*

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pragmatics relates to citizen engagement during crises to identify the key factors influencing engagement in short social media messages. In this context, we address the following research questions:

> *Research Question 1 (RQ1).* What social dimensions of communication are used by the local governments during crises? How do these dimensions align with the expected communication strategies during crises? How does engagement evolve over the different crisis phases?
> *Research Question 2 (RQ2).* Does the communication strategy adopted by governments drive citizen engagement across the crisis phases? If so, to what extent do the social dimensions of communication relate to engagement?

We propose a framework that combines and operationalises the above theories to assess the relevance of social intents as drivers of engagement. This combination is a novel and practical aspect of this work. Focusing on the COVID-19 crisis, we apply emergency management communication theories to provide an informational perspective of how governments adopt risk and crisis communication patterns over time [7]. Using a causal inference model, we examine the relationship between engagement and communication intents extracted from social posts during different crisis phases. Through various model iterations, we progressively assessed different predictors and confounding factors. Our analysis identified significant causal effects between the communication intents in social posts and citizen reactions. In addition, we observed prevalence patterns for specific social dimensions that aligned with expected crisis communication phases. This study highlights how communication strategies evolve during a crisis, reflecting different intents that drive citizen engagement. We believe our framework will aid governments and practitioners in monitoring and planning effective communication strategies.

The COVID-19 pandemic posed unique challenges for Latin America, a region characterised by a large population and significant health, social and economic management difficulties [8]. While most studies focus on developed regions like United States and Europe, Latin America has comparatively received less attention [4]. For example, although social media use has grown in Latin America, enabling citizens to stay informed and share opinions on social and political issues [9,10], few studies explore its role in crisis communications within this region. This situation underscores the importance of analysing social media engagement in regions with distinct socioeconomic contexts, where effective government communication during crises is crucial [11]. To address this, we instantiate the proposed framework and ground our study using a data collection from Argentinian local governments (i.e. municipalities) communications issues during the COVID-19 pandemic. Argentina implemented preventive measures before the virus was detected and intensified them with the emergence of cases, including strict lockdowns, flight cancellations, border closures, and mandatory face masks [12]. Despite these efforts, by April, Argentina had one of the highest numbers of infections, and by January 2021 it was deemed as one of the five worst countries to live during the pandemic [9]. Local governments were chosen due to their significant role in citizens' daily lives, both administratively and democratically [13]. This focus on communications in Spanish provides a broader perspective on social media use for crisis management, complementing research typically reported in English [14].

2. Background and related works

Communication during crises often focuses on risks. Risk communication involves exchanging information about the nature, magnitude, significance, or control of risks [15], such as those posed by the COVID-19 pandemic. Effective communication strategies are crucial for risk management as they can alert individuals to risks, inform them of protective measures, and increase awareness. Crisis communication research has primarily focused on United States and Europe [4]. However, cultural and political factors play a critical role in shaping crisis communication strategies and public responses. For example, in collectivist cultures, messages highlighting community well-being and solidarity tend to be more effective, while in individualist cultures, appeals to personal responsibility might be more impactful [16,17]. In addition, trust in institutions, media, and government varies across cultures, influencing the effectiveness of communications [9,17]. This emphasises the need for cultural knowledge, awareness, and skills in developing communication strategies that resonate across diverse cultural contexts [11], and enhance the effectiveness of the crisis communication efforts.

Crises are typically conceptualised in three phases: preparedness, response, and recovery [18,19]. The preparedness phase (pre-crisis) involves planning for emergencies before they occur. The response phase (during-crisis) entails implementing these plans. The recovery phase (post-crisis) involves actions to recover after the critical events. Although crises are often unpredictable, they follow a certain linear progression. Then, effective crisis communication strategies should consider the developmental phases of a crisis to lessen the uncertainty, respond and resolve the situation [20].

Social media is a ubiquitous communication channel, enabling rapid and effective message dissemination and bidirectional interactions [21,22]. People use social media not only to interact with each other but also to connect with companies, governments, and institutions. In particular, local governments increasingly use social media to engage citizens and involve them in public decisions [5,23]. Citizens might have diverse information needs and expectations from their government, so effective communication requires monitoring their perceptions. This implies tracking citizens' communication needs during crisis phases to ensure that messages align with their needs, values, and experiences [20]. Engagement is regarded as a cognitive and affect-driven state of mind [5], which, in social media, is expressed through different behaviours that can be tracked in user activity, responses, posts or communications within specific groups.

Message content significantly influences people. During crises, social media messages can provide timely information to reduce anxiety and stress, causing engagement levels to fluctuate. Then, it is crucial for crisis managers to monitor engagement to promote socially beneficial behaviours. Models and theories from social sciences offer conceptual foundations for such analyses. This is where models and theories from social sciences can provide conceptual foundations for different analyses. Several interesting works in this direction can be found in the literature. For example, Choi et al. [24] studied social media conversations and identified predetermined sociological elements (or dimensions) that characterise human relationships, based on Habermas' theory of communicative action [25]. This theory emphasises the pragmatic meaning of communication and the dialogic dynamics that engage participants in producing and understanding meaning.

The *uncertainty reduction theory* [26] argues that information is crucial in communication, especially when individuals feel uneasy about uncertain situations or phenomena. Thus, uncertainty is perceived as a motivating factor (for individuals) to seek information through interactions. As individuals interact and reduce uncertainty, positive outcomes such as attraction, liking, and stress reduction often occur. In crisis communications, this theory suggests that people need to stay informed about changing contexts and events to alleviate distress and uncertainty.

Linguistic analysis of social media content (e.g. tweets) is a key approach to understanding users' information needs, especially during crises. When it comes to a crisis, each phase might reflect different information needs [27]. From an information perspective, during the crisis response phase, people typically require concise, specific information to take immediate protective actions. In contrast, during the preparedness and recovery phases, people need detailed information either to increase awareness of upcoming events or to accelerate recovery activities and minimise adverse effects. Son et al. [27] used the media synchronicity theory to analyse tweet content according to expected needs during different crisis phases. Their findings suggested that tweets affect people differently based on how the government shares information, providing guidelines for crafting effective messages. Fissi et al. [3] analysed COVID-19 communications using an emergency management communication framework [7], identifying key topics and engagement patterns between citizens and the Italian government. Their findings highlighted the importance of specific topics during crisis phases and identified gaps between citizens' needs and government communication, often related to the timing of messages. Lindholm et al. [28] compared social media posts of health authorities and prime ministers in Nordic countries during the early months of the crisis revealing different communication intents. While health authorities focused on informative and instructional content, prime ministers aimed to provide support and appeal for solidarity. Hagen et al. [29] analysed tweets from the Zika outbreak in the United States, identifying communities and influential users through retweet graphs and network metrics while manually categorising topics like virus spread, prevention, and frustration with government responses. Lachlan et al. [30] studied hashtags during the pre-crisis phase of a natural disaster in United States, highlighting inconsistencies in hashtag usage and minimal government participation, without exploring engagement. Finally, Zhao et al. [31] assessed influential users in four corporate and political crises, focusing on tweet volume, network position and engagement, while overlooking the temporal dynamics and differences among user types (e.g. government vs others).

Chau et al. [32], Henríquez-Coronel et al. [33] and Arias et al. [34] analysed data in Spanish-speaking regions. Chau et al. [32] categorised earthquake-related tweets in Mexico (asking for help, searching for someone, offering support, making demands or suggestions, joking, and reporting bad news) and applied emotion analysis. Henríquez-Coronel et al. [33] examined tweets from three official organisations during the same crisis, classifying them into five categories (opinion, information, emotion, actions and technology). Informative tweets peaked on the first day, while opinions increased on the last. Finally, Arias et al. [34] conducted sentiment analysis on COVID-19 tweets in Panama, identifying weekly sentiment changes linked to pandemic events. None of these studies considered engagement.

Overall, we believe that the study of crisis communication on social media can be significantly improved by integrating sociological theories and models. Previous research in this area has primarily focused on the public's use of social media during crises, often employing descriptive methods such as trending topic extraction, sentiment analysis and word usage statistics through natural language processing (NLP) techniques [35]. While these methods provide valuable insights into public sentiment and discourse, they tend to overlook important content features such as intent and pragmatics, which can significantly influence user perceptions and engagement. Moreover, the majority of existing studies

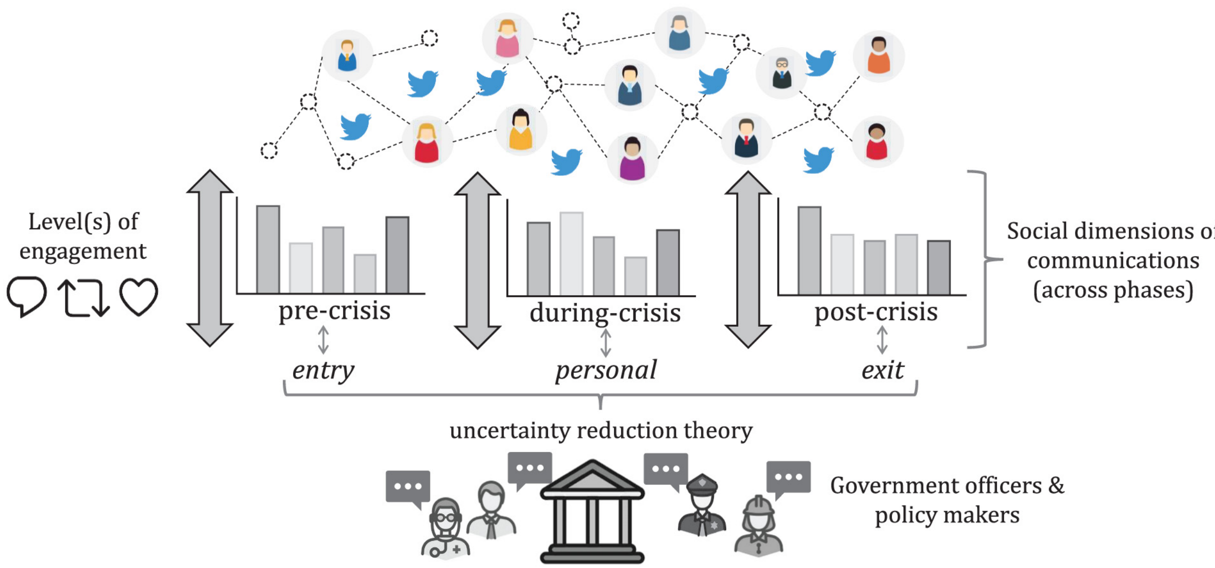


Figure 1. Conceptual elements of the proposed analysis framework.

have concentrated on the role of the public, with comparatively less attention given to governmental communication strategies, especially the social aspects of language pragmatics during crises, which is a key aspect of our approach. In this sense, our study shifts the focus towards governmental communication, specifically examining how local governments' social media communication strategies affect public engagement.

While semantics focus on the topics, communicative acts give shape to the nature of a relationship, as well as their perceptions over the relationship [24]. This distinction enables us to look beyond surface-level content and explore the underlying social dynamics at play. By examining communication for clues about relationship perceptions, we can explore additional sociological and psychological variables that may help us understand both online (and perhaps offline) user behaviour, including trust-building, solidarity and authority, which is crucial for understanding user engagement in times of crisis. We further extend this analysis by focusing on how these social intents evolve throughout the course of a crisis and how they relate to varying engagement patterns as the crisis unfolds. This perspective is not only novel but also necessary for capturing the nuanced ways in which communication strategies shape and are shaped by the citizens' engagement, especially within the complex sociocultural contexts of local governments. Our approach, therefore, contributes to a deeper understanding of how government communications can foster or hinder citizen engagement during crises, offering valuable insights for both scholars and practitioners involved in crisis communication.

3. Material and methods

Language and communication literature distinguishes between *what* and *how* people communicate [1]. Language can offer significant psychological cues about people's intentions and motivations. Social science models and theories offer conceptual foundations for analysing these aspects. Our goal is to characterise social media engagement through the lens of the *social intents of communication* and assess their relevance and variability over time. This variability can be linked to different crisis phases. We argue that this integrated view is crucial for governments to define or adjust communication strategies that foster citizen engagement and indirectly capture factors driving message propagation during crises.

Our analysis framework is outlined in Figure 1. Based on previous studies of government and citizen engagement through social media [4,36,37], we assume a flow of communications between local governments and citizens (*Twitter* users) during the evolution of a crisis. A key component of this framework is the model of social dimensions of communication proposed by Deri et al. [38], who leveraged NLP techniques to empirically identify social dimensions of communication that help understand intent in human communications. Grounded in Habermas' theory of communicative action [25], these dimensions represent the communicative actions occurring in a dialogue between participants, applicable to messages from government officers to citizens. We view citizen engagement as a function of these dimensions.

We assume a traditional crisis timeline with three phases: pre-crisis, crisis and post-crisis. The social dimensions of communication are present in each phase but are expected to have a different prevalence according to the specifics of

Table 1. Data collection details.

	Total	no-COVID	pre-COVID	during-COVID	post-COVID
#tweets	330,753	70,267	11,267	171,673	77,546
#tweets per municipality	41,34.41 ± 2909.53	878.34 ± 140.84	140.84 ± 111.91	2145.91 ± 1439.67	969.33 ± 1040.85
#original tweets (including replies and quotes)	304,972	65,023	10,358	157,866	71,725
Avg. original tweets per municipality	3812.15 ± 2740.02	812.79 ± 703.74	129.48 ± 105.78	1973.33 ± 1355.36	896.56 ± 979.88
#RT	25,781	5244	909	13,807	5821
Avg RT per municipality	339.22 ± 634.69	5244 ± 133.86	11.51 ± 22.14	174.77 ± 372	73.68 ± 222.33
Avg likes original tweets	10.42 ± 113.54	10.2 ± 69.21	13.12 ± 137.11	10.13 ± 112.5	10.86 ± 141.06
Avg replies original tweets	0.79 ± 4.55	0.45 ± 3.23	0.69 ± 3.57	0.9 ± 4.13	0.86 ± 6.27
Avg RT original tweets	4.79 ± 42.73	5.67 ± 29.67	6.22 ± 75.2	4.54 ± 44.49	4.33 ± 42.35
#original tweets per municipality with media	227,851	54,758	8552	110,755	53,786
#original tweets per municipality with mentions	52,503	13,602	1667	24,456	12,778
#original tweets per municipality with URLs	89,413	22,597	3577	44,043	19,196
#original tweets per municipality with hashtags	131,305	31,357	4979	66,618	28,351

each phase. To investigate communication content, we rely on elements of the uncertainty reduction theory to focus on specific dimensions over time. From this perspective, citizen engagement still depends on these dimensions but is also 'modulated' by the temporal factor of the crisis phases and the expected content features that reduce uncertainty.

We measure engagement using social media indicators such as popularity, commitment, and virality [4,13]. We then explore the relationship between engagement and social dimensions across crisis phases. Using a causal inference process, we extract dimensions from the textual information in social media posts (i.e. tweets). Afterward, we rely on a hierarchical causal analysis with a negative binomial model, treating engagement as the outcome and progressively assessing various predictors and confounding factors. The methodological steps of the study are described next.

3.1. Data collection

Several studies have highlighted the presence of local governments on social media [4,36,37], including in Latin America [39] and Argentina [40,41]. Our analysis uses tweet data in Spanish shared by the local governments of Buenos Aires province, the largest in Argentina. Buenos Aires was chosen due to having both the largest population and the largest proportion of politically active citizens, including at least 37% of the national electoral roll. We used *Twitter* (now *X*), as it is one of the most widespread social media sites, which serves as a global and real-time communication medium, thus providing a glimpse of contemporary society [42]. After manually searching, we found the accounts of 124 out of 135 municipalities in Buenos Aires. We retrieved user information and tweets for each account using a publicly available tool[1]. The data collection spans from 1 January 2019 to 23 December 2022[2]. We identified three crisis phases [18] based on Argentinian government decisions. First, a *no-COVID* phase up to 1 January 2020 when no COVID-19 announcements were made, serving as a control period to assess pre-crisis communication strategies. Second, an *Entry* or *pre-COVID* phase up to 1 March 2020, when the first COVID-19 publications started to be shared by government officials, with initial contagions announced on 3 March 2020. Third, a *during-COVID* phase up to 31 December 2021 during which Argentina enforced various policies and restrictions, including flight restrictions until the end of 2021. Finally, a *post-COVID* phase starting 1 January 2022 when most restrictions were lifted.

Out of the 124 identified municipalities, 118, 94, 103, and 90 shared at least one tweet in the *no-COVID*, *pre-COVID*, *during-COVID* and *post-COVID* phases, respectively. Only 80 municipalities were active across all phases. Table 1 summarises the statistics for these 80 municipalities[3]. The collection includes over 330k tweets from the selected government

Table 2. Dimension description (adapted from Choi et al. [24]).

similarity	Shared interests or motivations.
trust	Will to rely on the actions or judgements of others.
romance	Intimacy among people with a sentimental relationship.
social support	Giving emotional or practical aid, favours, companionship.
identity	Shared sense of belonging to the same group, culture, or identity that it is meaningful to them and could form a basis of their self. Need to belong.
status	Showing respect, appreciation, gratitude, or admiration to others
knowledge	The focal point is the symmetric or asymmetric exchange of ideas or information.
power	One party has more resources or the ability to control or influence the behaviour or outcomes of others.
fun	Experience leisure.
conflict	Contrast or diverging views.

accounts, with a higher proportion of original tweets (directly shared tweets, replies or quotes) than retweets across all phases. We focused on original tweets as they conveyed sufficient content for evaluating crisis management aspects. Tweets were slightly pre-processed to remove special characters, URLs, and mentions, while hashtags were kept without the numeral symbol and split into their constituent words. Spelling corrections were not applied since most tweets were correctly written, and abbreviations were rare.

The most common resources were media elements (58% of tweets), followed by URLs (40%) and hashtags (36%). Citizens interacted more frequently using likes (72% of all tweets had at least one like), followed by retweets (58% of all tweets were retweeted at least once), and replies (35% of all tweets received at least one reply). Interactions were higher in the *pre-COVID* and *during-COVID* phases, with over 84% of tweets receiving at least one reaction.

3.2. Operationalisation of theories

Operationalisation refers to mapping the conceptual elements of a theory to concrete, actionable elements that can be computationally analysed. We use the social dimensions model proposed by Deri et al. [38] as an operationalisation of Habermas' theory of communicative action, enabling the application of NLP and ML techniques to analyse textual messages like tweets. Deri et al. [38] identified ten major social dimensions: `similarity`, `trust`, `romance`, `social support`, `identity`, `respect`, `knowledge`, `power`, `fun` and `conflict`. These dimensions, defined in Table 2, serve as building blocks for social interactions. While not exhaustive, they summarise key concepts extensively studied in social and psychological sciences [24]. Deri et al. [38] provided empirical evidence that most people can define their interactions using these ten dimensions, confirming their relevance to interpersonal exchanges. Furthermore, Choi et al. [24] demonstrated that the dimensions can be extracted from text, with their combinations suggesting interaction intentions and community types.

Despite the unpredictability of crises, their development follows a certain linearity. Effective crisis communication strategies should consider these developmental stages to reduce uncertainty, respond effectively and resolve situations [20]. On this basis, we propose to operationalise the uncertainty reduction theory in terms of social dimensions and crisis phases, adapting it to assess crisis-related communications based on citizens' changing information needs [43]. The theory's three stages correspond to the three crisis phases [18]:

- *Entry* (*pre-crisis* phase). Communication focuses on clarifying basic information. As uncertainty rises, reciprocity and information-seeking behaviours increase, while intimacy decreases. The focus is on reducing uncertainty through familiar protocols and messaging, linked to the dimensions of `knowledge`, `status`, `trust`, `similarity` and `power`. Occasionally, if someone or something is to be blamed for the crisis, communications could also reflect the `conflict` dimension.
- *Personal* (response or *during-crisis* phase). As uncertainty decreases, individuals share personal attitudes, values, and beliefs, with reduced information-seeking and increased intimacy. Communication fosters interactive discussions, linked to `social support`, `status`, `identity`, `trust`, `similarity` and `fun` (as a reflection of emotions).
- *Exit* (recovery or *post-crisis* stage). Individuals plan for future interactions and define the 'new normal', increasing uncertainty and driving higher information-seeking and reciprocity, similar to the *Entry* stage. This stage is linked to the same social dimensions as the *Entry* stage.

As the dimensions model [24] is only available in English, the collected tweets in Spanish could not be directly analysed. Due to the lack of labelled texts in Spanish, re-training the model was not feasible. Although word embeddings share similar geometric relations across languages [44], using Spanish embeddings directly in the model was not viable because the English and Spanish embeddings were trained on different data sources, leading to mismatched semantic spaces[4]. To address this, tweets were translated into English using *Google Translate*, as Spanish translations were proven reliable for psychometric analysis [45]. A sample of translations was manually checked for quality and consistency[5].

The model generates a score indicating the likelihood of a text reflecting a given dimension. Scores can be computed for the entire text or averaged across sentences. Since tweets averaged 2.11 sentences (± .01), full-text scores were used to represent the dimensions, as they showed no statistical difference from sentence-average scores.

3.3. Measuring engagement

Engagement usually manifests as behavioural responses related to popularity (e.g. the number of likes a post receives), commitment (e.g. the number of comments or replies) and virality (e.g. the number of shares) [4,5]. Liking requires the least commitment and cognitive effort, often indicating agreement, support or a positive emotional state [5]. Replying and resharing involve higher levels of engagement and effort [5]. Commenting allows individuals to publicly express their views, co-create content and engage in discussions, facilitating two-way communication. Resharing can be seen as a form of self-expression that increases content visibility and reaches new audiences [5].

We primarily focused on popularity as the engagement indicator, using the number of likes as the main metric. This decision was based on data observations showing that likes, replies and retweets varied, as summarised in Table 1, with replies more sparsely distributed than likes and retweets.

3.4. Inference analysis

Each tweet shared by a government account reaches its citizens and may serve various communication purposes using resources like mentions, URLs and images. The context of the tweet (e.g. the government account sharing it, the number of followers and the time it was posted) can influence the type and intensity of citizen engagement. Although engagement may depend on various social processes, making exact estimations difficult [2], certain features typically induce more engagement. Then, we used a causal inference process to analyse the relationship between tweet characteristics and citizen engagement.

The number of likes is defined as the dependent variable, serving as a proxy for engagement. Since likes are count data with a discrete distribution, the assumption of a normal distribution cannot be verified and traditional ordinary least squares models are inadequate [46]. Poisson or negative binomial models are better alternatives for such data, especially when most data points are clustered at lower values. The main difference between them is that the negative binomial model accounts for excess variance, making it suitable for over-dispersed data (i.e. variance is much higher than the mean) [47]. We empirically confirmed the negative binomial model's superiority over Poisson using the Akaike Information Criterion (AIC) and the likelihood ratio test. All models were implemented in Python using the *statsmodels*[6] package. Numerical variables were centred from their means when applicable [48].

We built several hierarchical models to examine the influence of social dimensions of communication on citizen engagement. Models were defined separately for each identified phase, following this sequence:

- *Model 1: User control features.* Research [2,6,27] has shown that user profile features can influence user engagement. For instance, Sutton et al. [2] determined that the number of followers and followees positively influenced retweeting. These variables are time-invariant, meaning they remain constant across all tweets from the same user, and can indirectly identify them. Although these variables are not directly related to the shared content, they can influence engagement outcomes by enhancing internal validity and limiting confounding factors. We considered two possibilities: (1) one-hot encoding user IDs; and (2) including follower and followee counts. Since including user IDs yielded better model performance (lower AIC scores), we discarded the follower and followee counts.
- *Model 2: Model 1 + tweet variables.* Sutton et al. [2] found that hashtags positively impacted engagement, while Suh et al. [49] noted that mentions and the number of past tweets negatively affected it. Building on Model 1, we added tweet-specific variables, including the number of hashtags, mentions, URLs, and tweet length (in words). Although we considered including the number of past tweets (i.e. for each tweet, the number of tweets the user shared before), it was discarded due to multicollinearity concerns.
- *Model 3: Model 2 + social dimensions effects.* Building on Model 2, we incorporated social dimensions of communication as the main independent variables. Each dimension was represented by a binary score, categorising

tweets based on whether they strongly reflected a given dimension. Due to varying score distributions, a tweet was considered to reflect a dimension if its score exceeded the 85th percentile for that dimension [50][7].

- *Model 4: Model 3 + engagement variables.* Expanding on Model 3, we added engagement metrics based on prior research showing relationships between engagement types. For example, Jungblut and Jungblut [51] found that dialogical retweets and replies receive fewer likes than original tweets, while Marsili [52] suggested that retweets amplify the tweet's audience, potentially increasing other forms of engagement. Also, Son et al. [27] used the number of retweets to gauge tweet propagation velocity. When likes were the dependent variable, we included retweets and replies as predictors. Conversely, when retweets were the dependent variable, we included likes and replies.
- *Model 5: Model 4 + interaction effects.* Building on Model 4, we added interaction effects to evaluate whether combinations of variables have a greater impact on engagement than individual variables alone. For likes as the dependent variable, we assessed interactions between social dimensions and retweets and replies. For retweets as the dependent variable, we examined interactions between social dimensions, likes, and replies. These interactions could help reveal how certain features, such as social dimensions, influence engagement when combined with other metrics [6].

Our study uses causal inference methods, treating it as a 'text-as-treatment' problem. According to Feder et al. [53], three conditions should be met for drawing valid causal conclusions: ignorability, positivity and consistency. *Ignorability* requires the treatments to be independent of the counterfactual outcome. While the presence of social dimensions (the treatments) in a tweet is not random, local governments cannot control how citizens interact with the tweets. Therefore, choosing a particular social dimension for communication does not bias citizen engagement. In addition, since engagement is based on shared content, it is unlikely that unobserved confounders affect both the presence of social dimensions and engagement. *Positivity* refers to the probability of receiving a treatment being between 0 and 1. The model outputs the likelihood of a tweet containing or reflecting a social dimension, which is bounded between 0 and 1. Each element is analysed independently, allowing their association with any social dimension or combination of them. Finally, *consistency* ensures that potential outcomes for each element must be consistent at each treatment level, and one element's treatment assignment should not affect another's potential outcome. For this study, the models determining the social dimensions were trained on different data than that being analysed, ensuring no relation to the engagement outcome.

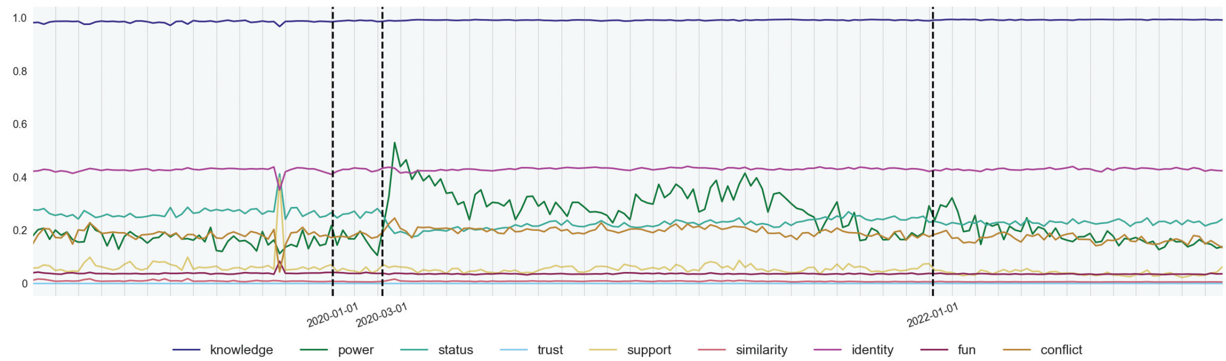
3.5. Data analysis

In this section, we analyse how government communication strategies during crises can be interpreted in terms of the social dimensions of communication and try to determine the contributions of those dimensions to citizen engagement.

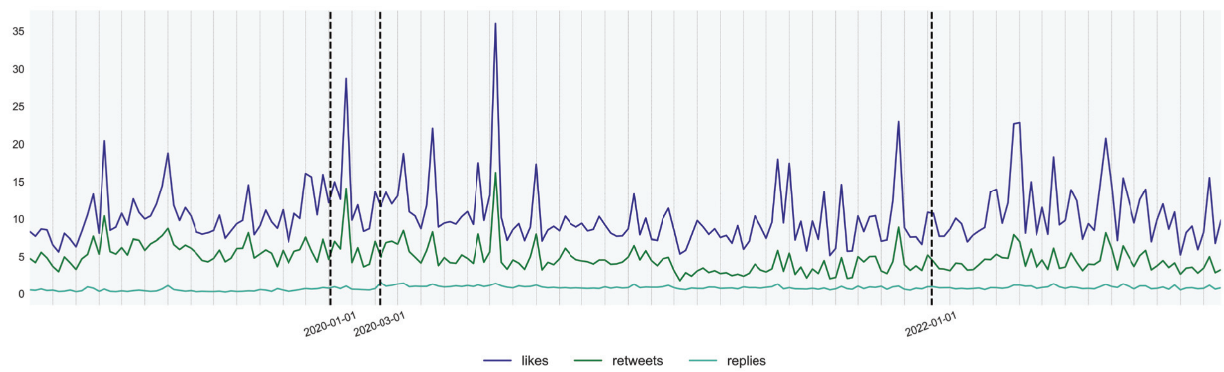
3.5.1. RQ1: Evolution of the social dimensions of communication during the crisis phases. As a context for answering this question, Figure 2(a) presents the temporal distribution of the social dimensions for the defined phases per week[8]. For each dimension, the weekly score represents the median score of the tweets shared that week. As it can be observed, the time series have some noticeable differences for some dimensions across the phases. We tested the statistical significance of the differences using an unpaired samples test and $\alpha = 0.01$.

We looked at the data at various time scales (e.g. individual tweets, daily and weekly) and were particularly interested in the phase transitions. In this regard, every dimension had significant variations when comparing the *no-COVID* phase with at least one of the COVID-19 phases. At the tweet level (i.e. each score represented a tweet), the transition between the *no-COVID* to the *pre-COVID* phases exhibited significant differences in `knowledge`, `status`, `trust`, `support` and `similarity`. At a coarse-grained time scale (i.e. daily or weekly scores), similar differences were observed with increased effect sizes, showing medium to large variations. In particular, `knowledge` increased its prevalence while the other dimensions slightly decreased it. This could imply that local governments focused on objectively sharing information with citizens at the beginning of the crisis.

In the transition from the *pre-COVID* to the *during-COVID* phases, small (significant) changes were observed for `power`, `status`, `similarity` and `fun`. In contrast, for the other dimensions, differences were negligible. In this case, `knowledge`, `power`, `social support`, `similarity`, `identity` and `conflict` increased their prevalence in the *during-COVID* phase, while `status` and `trust` decreased it. We can match the changes in `social support` and `similarity` to the transition between the *Entry* and *Personal* stages of the uncertainty reduction theory, by which conversations tend to turn more personal and related to attitudes and values. The high value of `knowledge` could stem



(a)



(b)

Figure 2. Temporal evolution of the social dimensions of communication and engagement across phases
(a) Temporal evolution of the social dimensions of communication across phases (b) Temporal evolution of engagement across phases

from the unprecedented nature of COVID-19 that required governments to continue communicating information as the knowledge of the virus evolved, and public-health policies were put in place. When moving from the *during-COVID* to the *post-COVID* phases, there were small changes in `power`, `similarity` and `conflict`, and negligible changes in `knowledge`, `status`, `social support` and `identity`. The dimensions of `knowledge` and `status` exhibited a higher prevalence than the remaining dimensions. This situation is aligned with the transition between the *Personal* and *Exit* stages, in which uncertainty raises (again), and communications revolve around `knowledge` and `trust`, as for the *Entry* stage.

In addition, we analysed the relationships between the social dimensions within each phase. To this end, we computed Granger causality to determine interaction effects among the social dimensions. During the *no-COVID* phase, multiple interactions were observed among almost all dimensions, which indicates that dimensions were highly correlated. Since none of the dimensions stood out, we could assume that no particular communication strategies for crisis existed (or that they cannot be distinguished). In the remaining phases, on the contrary, we observed interaction patterns around specific dimensions. For the *pre-COVID* phase, only significant interactions involving `knowledge`, `social support` and `identity` were observed, `knowledge` being a very relevant dimension of the *Entry* stage. Then, in the *during-COVID* phase, new interactions appeared for `knowledge`, `status`, `social support` and `trust`. In this case, `social support` and `trust` are two of the relevant dimensions of the *Personal* stage. Finally, in the *post-COVID* phase, most interactions were around `knowledge`, `status`, `trust` and `similarity`, among the relevant dimensions in the *Exit* phase. These observations align with the statistical analysis results, showing different prevalence patterns for the (individual) dimensions and groups of closely-related dimensions in particular phases. Thus, we can infer that local governments, either consciously or not (i.e. they planned the communication strategy according to the evolution of the crisis, in contrast to exercising a reactive style of communication based on the perceived needs), did not pursue the same communication strategy across phases, and that not only the prevalence or choice of individuals dimensions changed, but also how dimensions interrelate.

Figure 2(b) shows the weekly mean tweet engagement. Across all phases, at least 72% of tweets received some form of engagement. When considered separately, at least 64% of tweets in each phase received at least one like, 21% at least one reply and 54% at least one retweet. As indicated in Table 1, the engagement was lowest in the *post-COVID* phase. The most common overlap in engagement occurred between likes and retweets, with 50% to 61% of tweets receiving both, while replies and retweets overlapped less frequently, occurring in only 20% to 25% of tweets.

As the Figure shows, phases showed differences in engagement. As before, we tested statistical significance using an unpaired samples test. Significant differences were found at both the tweet and aggregated levels, with larger effect sizes in the aggregated weekly scores for all phases. When analysing transitions between phases, all engagement proxies showed significant differences at the tweet level. *Pre-COVID* had a significantly larger distribution of likes and replies that *no-COVID*, reflecting heightened citizen interest in local government communications. *During-COVID* showed significantly more replies than *pre-COVID* (but significantly fewer likes) and more likes/retweets/replies than *post-COVID*. At the weekly aggregated level, significant differences were observed only for replies between *pre-COVID* and *during-COVID* and for likes between *during-COVID* and post-COVID. Two engagement peaks appeared near the start and end of the *during-COVID* phase, while engagement was lower in between. These peaks likely correspond to key transitions: the onset of interactive communication in the `Personal` stage and the increase in uncertainty surrounding the `Exit` stage and the corresponding lifting of COVID-19 restrictions.

In summary, the analysis shows evidence that local governments focused on different social dimensions of communication across the phases of the COVID-19 crisis, thus showing an adaptation of their communication strategy across phases. There were variations in how dimensions were reflected in the communication across phases, and the relative interactions between dimensions within phases. The prevalent communication dimensions across crisis phases matched the expected communications according to the stages of the uncertainty reduction theory. These findings seem to indicate that the changes in governments' communication reflected crisis management actions. In parallel, engagement patterns also shifted across phases, with varying levels of likes, retweets, and replies aligning with changes across phases.

3.5.2. RQ2: Social dimensions of communication as drivers of engagement. This question focuses on how social dimensions relate to citizen engagement and whether their effects vary during the crisis phases. As mentioned, we used negative binomial models with engagement measured as the *number of likes* as the outcome and different predictors. Based on the defined models, we initially tested the variance information factor (VIF) to determine the existence of multi-collinearity among the variables. None of the VIFs exceeded the acceptable level of 5 [54], indicating that multi-collinearity was not a concern.

Table 3 presents the coefficients of the negative binomial model[9] for the best model computed for each phase. These models were chosen according to their AIC and log-likelihood ratio. Except for the *pre-COVID* phase, the best models included the user control and tweet variables, the engagement variables, the dimensions main effect variables, and the interaction variables (Model 5). In the *pre-COVID* best model, the interaction variables were not included (Model 4). We also report the Incidence Rate Ratios (IRRs) to ease the interpretation of the obtained coefficients.

The differences in AIC indicate that the quality of inferences for the phases varied, with the lowest quality models associated with the *during-COVID* phase. The *during-COVID* phase achieved the highest AIC; thus, it was the most challenging phase to analyse. This could be due to the extensive time span covered by the phase, which included the beginning of the pandemic and the first health-related policies, the strict lockdown, and multiple policy relaxations. At the same time, governments were also trying to 'learn' how to effectively interact with the citizens, introducing successive changes in their communication strategy, which might have affected the results.

For the *no-COVID* phase, regarding the tweet and engagement variables, only `#mentions` and `#urls` contributed negatively to engagement. The observations for `#urls` differ from those by Son et al. [55], who reported a positive relation between `#urls` and engagement. Three dimensions also contributed negatively (`power`, `fun` and `trust`). The largest contributors to engagement were `similarity` (IRR = 1.294), `knowledge` (IRR = 1.126), `status` (IRR = 1.155) and `conflict` (IRR = 1.140), followed by tweet-length (IRR = 1.111). On average, the tweet variables and the social dimensions contributed equally to engagement, with a small difference favouring the social dimensions. Regarding the interaction variables, including `#retweets` contributed more to engagement than `#replies`. While `#retweets` contributed positively to engagement (IRR = 1.056), the interaction variables including it contributed mainly negatively to engagement. Although the best model is among the most complex, solely considering the user

Table 3. Negative binomial coefficients for predicting citizen engagement. The top-5 predictors for each model are underlined. Stat. significance: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

		no-COVID	pre-COVID	during-COVID	post-COVID
Tweet variables	tweet-length	0.106*** ± 0.014	0.188*** ± 0.032	0.12*** ± 0.01	0.209*** ± 0.015
	#hashtags	0.012** ± 0.004	0.062*** ± 0.01	0.068*** ± 0.003	0.057*** ± 0.004
	#mentions	−0.027*** ± 0.005	−0.06*** ± 0.017	−0.029*** ± 0.006	−0.011 ± 0.006
	#urls	−0.207*** ± 0.01	−0.214*** ± 0.027	−0.208*** ± 0.007	−0.243*** ± 0.011
Dimension variables (main effects)	social support	0.017 ± 0.041	−0.049 ± 0.029	0.041*** ± 0.011	−0.174*** ± 0.051
	knowledge	0.119* ± 0.058	0.101** ± 0.035	0.048*** ± 0.013	−0.025 ± 0.018
	conflict	0.131* ± 0.052	0.131*** ± 0.036	0.095*** ± 0.013	0.274*** ± 0.04
	power	−0.084* ± 0.036	−0.066* ± 0.026	−0.044*** ± 0.012	−0.065*** ± 0.017
	similarity	0.258*** ± 0.052	0.084** ± 0.03	0.013 ± 0.012	0.038* ± 0.018
	fun	−0.173*** ± 0.047	−0.077* ± 0.034	−0.093*** ± 0.014	−0.064** ± 0.023
	status	0.145*** ± 0.042	−0.1** ± 0.038	0.074*** ± 0.014	0.108** ± 0.041
	trust	−0.146*** ± 0.034	−0.021 ± 0.037	−0.076*** ± 0.014	−0.135*** ± 0.034
	identity	0.041 ± 0.049	0.01 ± 0.034	−0.112*** ± 0.012	−0.038 ± 0.027
Engagement variables	#retweets	0.055*** ± 0.005	-	0.037*** ± 0.004	0.028*** ± 0.006
	#replies	0.029** ± 0.009	0.1*** ± 0.015	0.048*** ± 0.007	0.041*** ± 0.006
Engagement × Dimension variables (cross effects)	engagement: support	−0.001 ± 0.006	-	−0.009 ± 0.006	0.018 ± 0.01
	engagement: knowledge	−0.016* ± 0.008	-	0.02 ± 0.011	−0.002 ± 0.003
	engagement: conflict	−0.013* ± 0.006	-	−0.032*** ± 0.007	−0.025*** ± 0.006
	engagement: power	0.004 ± 0.005	-	−0.003 ± 0.007	−0.001 ± 0.002
	engagement: similarity	−0.021*** ± 0.005	-	−0.029*** ± 0.007	−0.004* ± 0.002
	engagement: fun	0.003 ± 0.007	-	−0.013 ± 0.01	0.004 ± 0.003
	engagement: status	−0.009 ± 0.006	-	0.024* ± 0.01	0.002 ± 0.007
	engagement: trust	0.01* ± 0.005	-	0.018 ± 0.01	0.014* ± 0.006
	engagement: identity	−0.002 ± 0.006	-	0.001 ± 0.007	0.003 ± 0.004
Model summary	AIC	322,940	53,688	763,607	316,210
	log-likelihood	−161,370	−26,750	−381,580	−158,000
	null log-likelihood	−217,630	−37,520	−524,080	−243,390

control variables achieved better AIC than models including the social dimensions and tweet variables. This implies that, at least for this ‘normal’ phase, communication intents by themselves were not enough to drive citizen engagement.

In the *pre-COVID* phase, the contribution to engagement of `tweet-length` (IRR = 1.206) and `#hashtags` (IRR = 1.064) increased. `#url` continued its negative trend towards engagement. Nonetheless, unlike the *no-COVID* phase, this observation agrees with the findings of Sutton et al. [35] and Lee and Yu [1], who also observed a discrepancy in the URLs effect when comparing non-crisis and crisis periods. In this regard, it seems that to increase engagement, it is preferable to include hashtags (which also facilitate search in social media) instead of URLs. Regarding the engagement variables, only `#replies` was included in the model, as considering `#retweets` also decreased the AIC value. This could imply a preference for dialogic-oriented conversations in which citizens value active interaction with governments, trying to get answers/replies to their uncertainties or comments. However, seven dimensions significantly contributed to engagement. `Knowledge` (IRR = 1.105), `conflict` (IRR = 1.140) and `similarity` (IRR = 1.087) contributed positively, while `power` (IRR = 0.936), `fun` (IRR = 0.925) and `status` (IRR = 0.904) contributed negatively. The negative contribution of `fun` could be due to the uncertainty of the situation after the announcement of the disease and the need for other types (or intents) of communication. All the dimensions linked to the *Entry* stage contributed significantly to engagement, except for `trust`.

In the *during-COVID* phase, the contribution of the tweet variables remained stable, while that of the social dimensions slightly decreased. In this case, only `similarity` did not significantly affect engagement. However, `social support` (IRR = 1.041), `knowledge` (IRR = 1.049), `conflict` (IRR = 1.099) and `status` (IRR = 1.076) had positive contributions, while `power` (IRR = 0.956), `fun` (IRR = 0.911), `trust` (IRR = 0.926) and `identity` (IRR = 0.894) exhibited negative ones. The sign change in `status` could be attributed to communications about thanking medical personnel and services, which became a daily tradition in many parts of the world. Only three interaction variables contributed significantly to engagement: `conflict` (IRR = 0.968), `similarity` (IRR = 0.971) and `status` (IRR = 1.023). Both conflict and status changed their sign when compared with the individual dimensions. These observations confirm the relationship between the different forms of engagement (in this case, `#replies` and `#likes`) and indicate that the communication intent might not be the only relevant factor as it might also be relevant whether citizens were also replying to such intent. When removing the interaction effects from the model (i.e. Model 3 or Model 4), the social dimensions changed their contribution to engagement. In the case of Model 4, all social dimensions contributed significantly to engagement. The largest changes were observed for `similarity` (IRR = 0.972), which showed a negative contribution. Slight changes were also observed for `power`, `trust` and `fun`. However, for Model 3, `conflict` (IRR = 1.130) showed the largest changes. In addition, a model including the social dimension and interaction variables but discarding the tweet variables achieved better AIC than a model including both the tweet variables and the dimensions, showing that interaction variables could contribute more to engagement than tweet variables. These comparisons hinted at the existence of multiple interactions between the selected variables and how they affect the inference capabilities of the model.

For the *post-COVID* phase, `conflict` (IRR = 1.315), `similarity` (IRR = 1.038) and `status` (IRR = 1.114) contributed positively to engagement, while `social support` (IRR = 0.840), `power` (IRR = 0.936), `fun` (IRR = 0.938) and `trust` (IRR = 0.873) contributed negatively. Note that `conflict`, `fun` and `status` increased their contribution compared with the *during-COVID* phase. On average, social dimensions contributed more to engagement than the retweet interaction variables. When transitioning from the *during-COVID* phase to this one, different from the analysis of the prevalence and interactions of dimensions, we did not observe changes in every dimension relevant to the *Exit* stage. Instead, most drivers for engagement were similar to those for the *during-COVID* phase. The only changes were `knowledge` (disappeared as a driver), `similarity` (appeared as a driver) and `social support`, decreasing its contribution (IRR = 0.840). However, `fun`, `status` and `trust` did not significantly change. When removing the interaction variables, small changes were observed in the contributions of each dimension. In this regard, although local governments seemed to follow communication guidelines for crisis management, citizen engagement was not always driven by them. This situation could be due to different citizens' perceptions about crisis status and information or support needs. This observation implies that defining a communication strategy is not enough and highlights the importance of considering how citizens react and express concerning the crisis to adjust the defined strategy. This situation was also reported by Fissi et al. [3], who observed discrepancies in the government's real and expected number of publications and the consequent citizen engagement, concluding that both government and citizens had different perceptions about the crisis timing.

At last, we replicated the analysis considering the number of retweets as the dependent variable. In this case, all best models included interaction variables with replies (*no-COVID* and *during-COVID*) or likes (*pre-COVID* and *post-COVID*). All best models included at least one engagement variable, except for the *pre-COVID* phase. The variables with the highest contributions were generally the same as for the previous analysis. Some exceptions were `status` that contributed negatively to engagement in every phase and `power` that only contributed significantly in the *during-COVID* phase. Overall, for the *pre-*, *during-* and *post-COVID* phases, the interaction variables contributed more to engagement than the individual dimensions. On average, the largest contributors to engagement were the tweet variables, except for the *during-COVID* phase, where the largest contributors were the engagement variables.

In summary, the analysis shows different patterns of contributions of the social dimensions of communication to engagement across the different phases. These patterns are attributed to changes in the government communication strategy and changes in citizen behaviours and interests. For some crisis phases, the models evidenced correspondences between the expected communication dimensions (from the crisis theories) and the drivers for citizen engagement. Although the influence of individual dimensions turned out to be not as strong as that of more straightforward variables (e.g. tweet features), we did notice that including the dimensions actually empowered their effects on engagement. This situation is compounded by the fact that engagement activities do not seem to work independently, and thus, there is an interplay between the dimensions and the engagement variables.

4. Discussion

Drawing on sociological, language, and crisis theories, we characterised government communication patterns through social media and their effects on citizen engagement in Argentina. Based on tweets related to the COVID-19 crisis, our study showed that local governments reflected different social dimensions of communication in their communication strategies across the phases of the crisis. According to the uncertainty reduction theory, the prevalence patterns for specific social dimensions resemble the expected communication stages during crises. From a theoretical point of view, this experience tells us that theories and models can be valuable tools for understanding crisis phenomena and social media, particularly if they can be adequately operationalised. In this sense, our analyses contextualise the traditional phases of a crisis and relate them to the uncertainty reduction theory, showing the correspondence of social theories to interactions in social media. Based on our inference analysis, we found that the reflected dimensions contributed differently to citizen engagement across crisis phases, which is explained by fluctuations in the communication strategy, but yet more importantly, by changes in the citizens' behaviours and interests.

Returning to the original question of *when* and *how* crisis communications are managed, we determined interesting effects between the dimensions identified in the tweets and the engagement level in the social network. For example, `knowledge` was a high contributor in the *pre-* and *post-COVID* phases but did not show up in the *post-COVID* phase, in which `status` appeared to be more relevant. As another example, certain dimensions always showed a negative contribution to engagement, such as `trust`, which could refer to empathy or interacting at a personal/intimate level with others. While these are interpersonal and close relations factors, they were not as relevant during a crisis. From a practical perspective, these examples highlight the importance of analysing the factors (e.g. dimensions and tweet features) that enhance or inhibit citizen engagement, considering the rapid development of crises.

This study offers valuable insights into how governments can use social media to foster citizen engagement, an increasingly important yet underexplored area, particularly in crisis contexts and developing countries [9,10]. We examined how citizen engagement evolved across different crises phases, highlighting changes in communication behaviours between governments and citizens. These findings are crucial for designing effective communication strategies during crises, where the dissemination of reliable information is critical. Although this study focuses on the COVID-19 pandemic, the proposed analysis is adaptable to any large-scale data streams such as other crisis or emergency scenarios, as similar communication patterns might be likely to emerge. The findings have practical implications for local governments aiming at enhancing their crisis communication strategies. This study emphasises the importance of understanding and leveraging the role of social media as a vital communication platform for crisis management. By understanding the social intents behind their messages and how these intents (and other features like hashtags, mentions and URLs) influence engagement, local governments can refine their communication strategies to build trust, foster solidarity, and encourage compliance with public health measures. Similarly, governments can use insights from engagement patterns to identify gaps in their communication, such as underrepresented groups or declining trust, and design more inclusive and responsive communication strategies. Real-time engagement analysis further enables dynamic adaptation of communication strategies as crises evolve. This study also highlights advancements in using social media as a two-way communication platform, contrasting earlier findings of low interactivity [4]. For example, Argentinian municipalities effectively used *Twitter* during the pandemic, demonstrating the value of sustained two-way communications even beyond immediate crisis needs. By addressing community concerns in addition to disseminating information, governments can foster collaboration and shared responsibility, ultimately improving outcomes during crises.

5. Conclusion

In this work, we studied the linguistic style and the pragmatic meaning of communications by linking a social communication model with the crisis phases and uncertainty reduction theories. We analysed a data collection from local governments in Argentina. Our findings show that the governments reflected specific patterns of social dimensions of communication in their communication strategies across the COVID-19 crisis, matching the expected crisis-related stages from the chosen theories. Then, we performed a causal inference analysis to determine how those patterns contributed to citizen engagement. The analysed models showed different patterns of contributions of the social dimensions of communication to engagement across the different crisis phases. In addition, for some phases, the models evidenced correspondences between the expected communication (as prescribed by the theories) and the drivers for citizen engagement.

5.1. Limitations

While this study provides valuable insights into crisis communication strategies, several limitations should be acknowledged. First, the focus on local governments in Argentina may limit the generalisability of the findings to other cultural, political, or crisis contexts. Crisis communication strategies are shaped by specific sociopolitical environments and outcomes may vary in countries with different institutional structures or communication norms. Second, the analysis relies exclusively on *Twitter* data. While *Twitter* was the second most-used source for COVID-19 information among Argentinians in the most populated provinces [9], with 52% of respondents using it (compared with 19% for *WhatsApp*, 16% for *Facebook* and 13% for *Instagram*) it does not capture cross-platform dynamics or offline communication efforts. Nonetheless, we believe our study accurately reflects *Twitter*'s communication patterns and provides valuable insights for crises communications. Third, relying solely on social media data excludes populations with limited access to digital platforms, potentially biasing representations of citizen engagement. Finally, translating tweets from Spanish to English may have introduced translation bias. Machine translation tools, while generally effective, can alter nuances, tone, or cultural context, potentially distorting the tweets' intended meaning when analysed through the dimensions model. Although this risk is mitigated by the well-written nature of official tweets, linguistic subtleties specific to Spanish may still be lost. Addressing these limitations would enhance the understanding of crisis communication and expand the applicability of these findings.

5.2. Future research directions

Building on the study's findings and limitations, several directions for future research can be identified. First, the study treated local governments as a homogeneous group, overlooking significant variations in demographic, socioeconomic, and cultural contexts, as well as differing responses to the COVID-19 crisis, which might have biased the results. Future research could stratify governments into more homogeneous groups based on shared characteristics (e.g. population size and socioeconomic conditions) and analyse them separately. In addition, more granular temporal divisions could be explored, such as sub-phases within the major phases (e.g. within the *during-COVID* phase), to account for varying tweet volumes and engagement patterns over time. Similarly, the study could be replicated across different cultural and regional contexts. For example, analysing how local governments in other Latin American countries managed crisis communication on social media could reveal cross-cultural differences and highlight best practices that are universally or locally effective. Second, we solely relied on *Twitter* data, which, while valuable and with a substantial user base, may not fully represent the broader population. Future work could include other platforms, such as *Facebook* or *Instagram*, where local governments maintain an active presence, to provide a more comprehensive view of crisis communication strategies across platforms. Third, the study used the social dimensions model proposed by Deri et al. [38] designed for English and applied it to Spanish-language tweets via translation. To address potential translation bias and preserve linguistic and cultural nuances, future work should focus on developing and validating resources and models specifically tailored to Spanish. This includes creating Spanish-specific embeddings and adapting the dimensions model to better capture the nuances of Spanish-language communication.

Fourth, future research could explore more advanced models that consider interactions between social dimensions and engagement, particularly those that consider feedback loops, where communication patterns influence engagement, and engagement, in turn, affects subsequent communication strategies. For example, it could be explored how engagement patterns, such as spikes in likes or replies, influence shifts in tone or social intents and how these shifts subsequently affect engagement. Counterfactual analyses could be conducted to evaluate the effectiveness of alternative communication intents during different crisis phases. For instance, it could be simulated how prioritising empathetic or reassuring messages instead of purely information communication might have impacted engagement over time. Fifth, machine learning models could be developed to estimate engagement levels based on the prevalence of the social intents, and other features such as sentiment, tone, readability, and the use of hashtags, mentions, or multimedia elements. By integrating natural language processing and engagement analytics, such models provide governments with actionable insights to optimise communication strategies. Sixth, future work could extend beyond the traditional engagement metrics used in this study to investigate the content and tone of citizen responses through replies and quotes. This deeper analysis could uncover patterns of sentiment, support, criticism or resistance to governmental messages. Furthermore, combining sentiment analysis with network analysis could reveal how responses spread within communities, offering insights into public opinion dynamics and the formation of collective attitudes during crises. By addressing these research directions, future studies could deepen our understanding of crisis communication, enabling governments to develop more adaptive, inclusive and effective strategies during crises.

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Ethical statement

Research is based on publicly available *Twitter* data initially collected by the authors. All data were collected in accordance with Twitter TOS. The study only considered data shared by public local government accounts. No user personal information was included in the analysis, and no user identity or private information is disclosed. As per Twitter TOS, the shared data only includes user and *tweet* IDs and aggregated content features.

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Notes

1. Faking it! https://github.com/knife982000/FakingIt
2. The full collection starts on 5 October 2009 and includes over 666k tweets, however due to the differences in the number of shared tweets in such period, and the lack of a clearly defined communication strategy, we opted for only considering tweets shared during 2019 and after.
3. GobBsAsTweets Twitter Dataset of Local Governments in Buenos Aires (Argentina) [56].
4. This was confirmed by a manual inspection of a sample of the embeddings.
5. Tweets were also manually analysed after processed by the model. Tweets representative of each social dimension, covering low, medium, and high prevalence levels were manually selected to assess translation accuracy and minimise potential biases.
6. https://www.statsmodels.org/stable/index.html
7. This threshold was selected following other works in the literature [50] also using Choi et al.'s [24] model to characterise social media posts.
8. Additional figures summarising scores, at the day level, the full set of coefficients, a set of pre-processed data, and the code for reproducing the analysis can be found in the following companion repository: https://github.com/tommantonela/citizen-crisis-engagement.
9. Although the estimated coefficients of control variables are unlikely to have a causal interpretation themselves, for the sake of clarity, the coefficients for the user control variables are included in the companion repository.

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