Computational Analysis of Communicative Acts for Understanding Crisis News Comment Discourses

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Abstract. Social media analyses using computational methods are becoming increasingly important, especially for crisis communication and social media monitoring. We seek to investigate the validity and utility of computationally analyzing communicative acts in social media crisis news comment discourses. We implement an applied act classifier for a novel online context by utilizing few-shot learning and a small manually annotated dataset. To illustrate the usefulness of analyzing communicative acts, we show that how people use acts in comments notably changes across the crisis timeline. In contrast to classic crisis research, early social media crisis responses in our study do not show a heightened use of acts oriented to discursive struggle only, but instead resolution oriented acts are most common at first. In further analysis, we show that computational analysis of acts can complement traditional content analyses to reveal more specific insights on the functions and goals of comments. Our study paves the way for more fine-grained approaches to understanding social media discourses and crisis responses, offering potential new tools for crisis management.

Keywords: Crisis Discourses · Crisis Narratives · Communicative Acts · Few-shot Learning · Applied NLP · Social Media.

1 Introduction

With the increasing use of social media as a communication tool and source for news, the capability for researchers, communication experts, and journalists to analyze the interactions taking place has become essential for understanding emerging narratives, perspectives, interactions between networks, and how opinions are formed. We argue that analyzing what acts social media comments represent can allow insights into how social media responses or reactions to crises evolve and how online participants position themselves toward emerging issues.

Computational modeling of communicative acts has not so far been widely applied to analyze social media interactions in crisis settings. We argue that such analysis can reveal what functions online comments have, allowing more fine-grained understandings of their position to the crisis in contrast to e.g. classic topic modeling. There can be significant differences in comments' functions although their contents might be quite similar, e.g.: 'What are politicians planning to do?' vs. 'Politicians are planning to do nothing!'. In this applied study, we explore if the analysis of communicative acts can be used to uncover broader changes in audience reactions to crisis news during a long-lasting crisis.

The identification of communicative acts is an important step towards a deeper analysis of social media comments. Natural Language Processing (NLP) can help unveil how acts are used in online turns to mobilize reactions or appeal to others [21], [35]. Although dialogue acts found in telephone and synchronous chat conversations have been extensively researched [5], [16], [22], [26], [34], how communicative acts appear and evolve in asynchronous conversations, e.g. in relation to crisis discourses, has not been researched much as of yet, despite its viability for investigating the dynamics of online discussion [38], [44].

Social media is relevant during crises as a communication medium, because key information travels fast through social networks [28]. For this reason, this paper focuses on online reactions to COVID-19 crisis news on the Indian NDTV and Canadian CTV channels on YouTube. We are interested in discovering whether differing positions can be found in comments to crisis news at different stages of the crisis, and whether they show an early discursive struggle as outlined in crisis research [41], seeking to answer three research questions (RQs):

- RQ1: Are there significant differences along a crisis timeline in terms of what type of acts comments represent?
- RQ2: Is there a discursive struggle visible in the comments at the initial phase of the crisis?
- RQ3: Can analysis of communicative acts using NLP be applied to complement content analyses to gain deeper insights into reactions to crisis news?

As there are no pre-existing models or datasets for act classification for asynchronous data such as ours, we form a theory [38], [9], [25] and data-driven annotation scheme , and train a classifier. Then, we use act-tagged data to conduct a time-series analysis of acts used in crisis news comments during three significant phases of the COVID-19 crisis: the beginning phase (Phase 1), the vaccination phase (Phase 2), and the prolonged phase (Phase 3). We analyze how act-taking changes along the crisis timeline and use acts to complement a further content analysis of central topics of the comments.

2 Communicative Acts in Asynchronous Conversations

Research concentrating on applying NLP to the analysis of social media has often focused on content-based approaches like topic modeling, Bag-of-Words or word or sentence vectors (e.g. [37]), or analyses of key accounts sharing content [20]. Social media comments have specific functions in relation to the content they are responding to – whether a comment is, e.g., stating information or asking for it considerably influences how its content should be interpreted. Acts represent what the main functions of a comment are within a conversation, i.e. what it does and how it relates to other actions taken in previous comments [9], [25]. Previous studies show that the concept of communicative act [25] can be used to analyze e.g. conversational flow, functions of comments, accountability, positioning, intentionality [21], [35], and conversational breakdowns [38].

Dialogue acts and intent recognition have been central interests to developing bots' and service agents' capabilities to interact with humans [19], and many datasets and annotation standards have been developed for computational identification of acts in synchronous chats [16] and telephone conversations [22]. These, however, reflect a context different from asynchronous conversation. We focus on communicative acts found important in earlier qualitative studies of asynchronous online conversations, especially from the point of view of political and crisis-related online discussion [3], [25], [38] Based on the theoretical foundations of acts[42], previous CMC research [38] and typologies of common acts [9], [25], we form an annotation scheme for acts that can account for the characteristics of asynchronous conversations related to crises and political discussions involving discursive struggle (see Table 1).

3 Crisis News and Social Media Discourse

People are increasingly using social media for news [48]. It is often an important tool for news actors, organizations, and crisis communicators for rapidly disseminating important information about the crisis [28], and for public for getting real-time updates on the crisis event(s), sense-making and mobilization [28]. Societal crises create an empty discursive space, requiring explanation regarding the crisis, related risks, and required mitigation actions [41] . This also makes such events vulnerable to manipulation [45] , which is why there is need for more fine-grained computational approaches to understanding crisis discourses online.

Researchers examined various aspects of social media discourses: besides investigating the content of messages, analyses of actor networks and behaviors can offer deeper insights into online interactions [20]. However, studies have often relied on content-based analyses [37], [45] . Not many applied studies have looked deeper into conversational behaviors like acts used in social media comments, although these insights can offer valuable information on citizen perspectives, positions, and conversation dynamics [38]. Such analyses can arguably provide more insight into how crisis narratives and discourses evolve on social media, and how the public is positioned to the ongoing crisis.

Acts are central, because crises are socially constructed by using acts in comments [29]. At the surface level, contributions to sense-making in news comments are formulated as communicative acts, which reflect how people position themselves to crisis news and what the function of each comment is [14], [25], [42]. Crisis discourses are seen to first involve an empty discursive space, where discourses struggle for visibility and legitimacy to explain the event [41], [30]. This is followed by a resolution of the struggle, one main narrative taking governance

[41]. Theories in linguistics also stress that discursive struggle is essential for establishing a main narrative on events, but some divide this into several phases, including orientation–complication–evaluation–resolution [32] , in contrast to crisis research [41], which mainly highlights the struggle and its resolution. We take inspiration from these theories in our empirical analysis.

To sum, we see investigating changes in the use of communicative acts that contribute to crisis sense-making as an opportunity to better understand shifts in perspectives to the ongoing crisis. Furthermore, we expect that this enables the identification of critical points of discursive struggle.

4 Data

We are interested in crisis news comments due to their role in shaping people's perspectives on a crisis, e.g. dissenting comments on news on social media may persuade people to orient toward the news source negatively [48]. We are especially interested in how news audience discourses around the crisis develop during a long-lasting crisis. YouTube news channels' crisis news videos and their comments offer an opportunity to investigate how reactions to the news change over time. We analyze comments on NDTV News' and CTV News' YouTube channel videos related to the COVID-19 crisis in India and Canada. The channels and their comments are mostly in English. We concentrate here only on English content, excluding all non-English content (mostly in Hindi in NDTV data), by using Fasttext [31]. The data were collected using scraper scripts in Python and the Google YouTube API. The data include comments to videos from *Phase 1*: the beginning phase (1/2020–8/2020), *Phase 2*: vaccination phase (02/2021–08/2021), and *Phase 3*: the prolonged phase of the crisis (11/2021–02/2022).

NDTV was selected as it is among the most followed English-language public news providers in India and one of the most trusted [36]. The channel allows viewer comments, and has a wide viewership. We were interested in the Indian context as trust in news has been reported to be low [36], and because Global South perspectives have not been sufficiently represented in research. To contrast this data to another English-speaking context, we compare the NDTV data to similar CTV data. CTV News was selected due to being among the most trusted news providers in their region, quite highly trusted overall, being mostly neutral in political ideology and considered to provide highly factual reporting[3]. It was an interesting context to focus on due to some of the events that occurred during the Pandemic in Canada, e.g. the Convoy movement. We wished to compare stretches of time during the long-lasting crisis that generated a lot of interest. To identify these, we investigated peaks in Google Trends on people's search habits related to the Pandemic, using search terms including "Corona, Coronavirus, COVID-19, COVID-19 vaccine, Pandemic". This allowed us to identify three phases where interest in the crisis peaked, as illustrated in Figure 1.

NDTV data has 216,455 comments to 1,942 videos in total. This includes 70,520 comments and 641 videos in Phase 1; 112,510 comments and 658 videos

[3] https://mediabiasfactcheck.com/ctv-news/

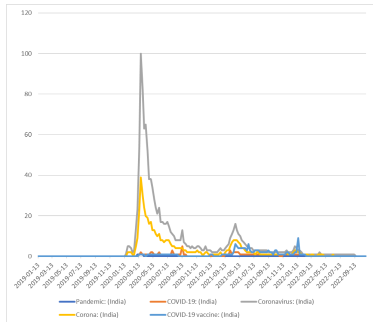

Fig. 1. Pandemic search term Google Trends from Dec. 2019 to Feb. 2022.

in Phase 2; 33,425 comments and 643 videos in Phase 3. Approximately 71% – 84% (depending on Phase) of comments were in English. 2% only contained emojis. The CTV set has 195,316 comments and 855 videos in total. These include 40,360 comments and 346 videos in Phase 1; 66,566 comments and 265 videos in Phase 2; and 88,390 comments and 244 videos in Phase 3.

5 Annotation Procedure

To our knowledge, there exist very few asynchronous conversation datasets manually labeled for acts. Existing models we found (e.g., [46]) have not included some key acts for analyzing crisis discourses: although challenges are included in [5], there exist no datasets with all relevant acts we need, e.g. challenges and denials [38], [3]. Based on our own experiments, classifiers trained on instant chat conversations [16] do not generalize well on asynchronous data. Thus, we chose to annotate a small dataset to train a model to fit our empirical case. Our annotation scheme is based on earlier research on acts found relevant in (crisis-related) asynchronous discussion [25], [38]. The data for manual annotation was selected randomly from the whole dataset, using Python scripts, making sure that each comment was used only once. We also ensured that the annotation data would have an equal distribution of comments from each phase.

According to research on digital conversation, a forum post may contain several acts [21]. This way, participants can achieve more by writing several points at one go [44]. Thus, we decided to prepare both single and multilabel annotations for the data. We assigned an order of importance and a confidence score from 1 to 5 to each comment. These were used in FlairNLP model training [24]. In annotation guidelines, we followed the descriptions of acts in Table 1[4].

We conducted the annotation iteratively: we, the authors, acted as the two annotators, continuing to annotate practice data until we had reached over 80%

[4] See the annotation guidelines in detail on our GitHub page: https://github.com/Aalto-CRAI-CIS/CrisisNarratives.

Table 1. Summary of acts used in our final action labeling scheme.

First act	**Description**
Question	requests information, expecting an answer providing or confirming the information.
Statement	asserts a fact or claim; provides information, evaluation/opinion announces information; answers a question (informatively).
Challenge	contests the epistemic basis of prior claims, actions, or feelings; or conveys a negative complaint, attributing responsibility for an event to a person or a group (accusation).
Request	proffers a service for the speaker, expecting acceptance/rejection. This class also contains proposals, both being directives.
Appreciation	includes various forms of positive evaluative reactions and thanking that can invite a response but do not require it.
Responding act	**Description**
Acceptance	marks the degree to which a speaker accepts a proposal, plan, opinion, or statement; or admission admitting that *e.g.* a statement, proposal or accusation is justified.
Denial	marks the degree to which a speaker resists, denies or rejects some previous proposal, plan, opinion, or statement; or contests some information or an accusation.
Apology	Excuse or apology for speaker's previous actions or statements.

agreement. We independently annotated the same set of comments (first batch 96 comments), compared and negotiated our annotations and resolved all conflicts, analyzing especially difficult cases to improve our guidelines and scheme. Then we proceeded to batches 2–3, following the enhanced guidelines and the same process. After batch 3, we had achieved a sufficient percentage agreement (80%).

For the final set, we calculated inter-annotator agreement scores to evaluate our annotation, using Krippendorf's alpha with the MASI metric to calculate the distance between annotations [2], and Fleiss Kappa (multikappa for multi-label) [15], using NLTK's agreement metrics package [4]. For the single-label task – considering only the first annotation – we achieved 0.75 Fleiss Kappa (substantial agreement). Krippendorf's alpha for the single-label task was 0.75, at the upper bound for acceptable agreement. For multi-label annotation, we achieved a Krippendorf's alpha of 0.64, and a Fleiss' Kappa (multikappa) of 0.60. We considered the overall percentage agreement and inter-annotator scores sufficient for our analysis study, and thus we moved on to labeling our dataset. A total of 676 comments were included in the manually annotated dataset. We used 60% for training, 20% for development, and 20% for testing. As for the multi-label option in annotation, analyzing the final annotated dataset, we found that most comments were assigned two labels. 64.2% of the comments were annotated with two action labels, 35.8% with only one action, and 6.7% with three actions. Four labels or more were very rare for our data.

We compared the effects of using different numbers of classes: original set of 13 acts – including accusation, announcement, rejection, admission, and evaluation along with actions in Table 1 – to compare if merging classes that had similar functions in our data would affect performance. We compared these to models trained with 9 acts (with accusations as a separate class), and models trained with 8 acts in Table 1.

6 ML Models and Analysis Methods

A common problem with applied analyses is that pre-existing models or labeled datasets do not fit the context of the case at hand. This can often become an obstacle to producing a high-performing model that suits the empirical context, and can be implemented rapidly enough to investigate constantly evolving crisis discourses. For this reason, we utilize few-shot learning to train our applied model. Few-shot learning is a viable solution for applied models, allowing the training of a model with novel classes by using a small, manually labeled dataset. In few-shot learning, a model is trained with a small set of labeled data to direct predictions in the novel applied task [43]. At the time of inference, the predictions of the model are based on a few manually labeled examples. Adapting pre-trained models for novel tasks utilizing few-shot learning has become possible with the publication of the latest large Transformer-based LMs like BERT [13] and GPT models [6], as many LMs have learned a variety of tasks implicitly in their training on immense text datasets, allowing generalization beyond their original uses. The common approach of fine-tuning a general language model like BERT for a novel task (*e.g.* RoBERTa [47]) has been shown to be outperformed by some more recent few-shot learning approaches [24].

We were interested in state-of-the-art models that would support multiple languages, multi-label classification, easy adaptation for applied use, and light use of resources. There is an increasing amount of models that allow multi-label few-shot learning [24], [43], [26]. FlairNLP [24], PET [40], Fastforward few-shot learning[5], and SetFit [43] and adapter methods [27] met our requirements.

FlairNLP proposes utilizing novel annotated examples, but also the information contained in the names of the novel classes (*e.g.* politics) [24]. It also allows the use of confidence scores in training and achieves high reported performance trained only with a low number of examples, supporting multiple low-resource languages [24]. Our chosen FlairNLP model uses the TARS Classifier 'tars-base' [24]. PET or iPET utilizes Pattern-Exploiting Training, which is a semi-supervised training procedure that reformulates input examples as cloze-style phrases [40]. Fastforward pipeline relies on a relatively simple algorithm using BERT and words2vec to embed the texts. SetFit is an efficient state-of-the-art framework for few-shot fine-tuning of Sentence Transformers [39] without the use of prompts that can require a lot of manual labor. It can achieve high accuracies using only a small set of manually labeled data [24]. For SetFit, we use paraphrase-Mpnet-base-v2 [39] as a base model. We also experimented with other models, including the Albert-small-v2 model [39], but their performance

[5] https://github.com/fastforwardlabs/few-shot-text-classification

remained lower. Lastly, PEFT methods deliver performance similar to that of pre-training and full fine-tuning in downstream tasks while using fewer resources. Various PEFT techniques include prompt tuning, Low-Rank Adaptation (LoRA) [27], and adapters [33]. Adapters, which insert small tunable modules into each transformer layer, have proven effective across different domains [33]. Adopting a similar approach to Mahabadi et al. [33], we train an adapter model with T5[6], a state-of-the-art transfer learning model [10]. We used Optuna [1] for hyperparameter optimization for all models.

In an initial test, SetFit and the adapter model had the best performance, FlairNLP third. We decided to focus mostly on SetFit and to drop PET and Fastforward due to the laboriousness of the prompt-use required in training, and low performance. As shown in Table 3, the T5-base adapter model (Adapt.T5) performs best, overall. For multilabel models macro-F1 best represents model performance, also better reflecting performance in our case where there is a class imbalance in data distribution. The best model performs sufficiently well on all our action classes based on closer examination. We resolved to use the T5 multilabel model as the most suitable option due to good Macro-F1 performance, and the fact that comments often included more than one action.

Table 2. Model performances in 5-fold cross-validation with single and multilabel classification using different numbers of acts

Model	**Act set**	**Single label**			**Multilabel**		
		Macro-F1	***Micro-F1***	***Acc.***	***Macro-F1***	***Micro-F1***	***Acc.***
Adapt.T5	8-act	**0.81**	**0.76**	**0.76**	**0.83**	**0.78**	**0.78**
Adapt.T5	9-act	0.70	0.74	0.74	0.76	0.72	0.72
Adapt.T5	13-act	0.48	0.74	0.74	0.49	0.68	0.68
SetFit	8-act	0.69	0.69	0.70	0.71	0.75	0.41
SetFit	9-act	0.67	0.68	0.69	0.64	0.70	0.37
SetFit	13-act	0.59	0.57	0.59	0.54	0.61	0.26
FlairNLP	8-act	0.67	0.59	0.64	0.70	0.72	0.27
FlairNLP	9-act	0.66	0.61	0.65	0.68	0.69	0.37
FlairNLP	13-act	0.54	0.58	0.57	0.58	0.59	0.18

To answer our RQs, we tagged our data with acts using the best ML model – the multilabel T5-base adapter model (Adapt.T5) with 8 acts. We extracted comments from the data pertaining to the three Phases of crisis on a week-by-week basis. We analyzed the frequencies of acts taken during each week divided by the total number of acts taken that week. We then plotted the time series analysis according to each act group's difference from group mean during each phase. We further investigated significant peaks in each act group, calculating an outlier threshold of $mean(G) + 2 \times SD(G)$ to indicate peaks that should be

[6] Hyperparameters: learning rate= $3e-4$, AdamW with linear learning rate, schedule with warm-up, batch-size 32, epoch number 200, without early stopping.

studied further. We excluded any weekly data that had less than 100 comments. To answer RQ3, we further analyzed significant peaks in the use of specific acts, using BertTopic for topic modeling [23].

7 Results

As indicated by our RQs, we aimed to show that communicative acts can provide meaningful insights into social media crisis discourses: showing significant changes in which acts would be most prevalent at different points in time (RQ1), confirming if early crisis involves discursive struggle (RQ2), and illustrating how different acts might involve different topics (RQ3). To answer RQ1, we wished

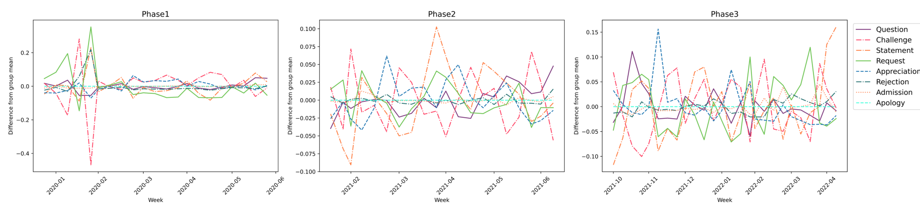

Fig. 2. Temporal differences in the use of acts during Phases 1, 2 and 3 in NDTV comments.

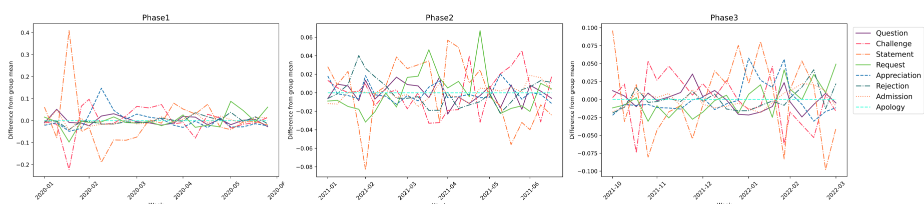

Fig. 3. Temporal differences in the use of acts during Phases 1, 2 and 3 in CTV comments.

to see if the relative use of acts would differ along the crisis timeline during three significant time phases, comparing the results from NDTV and CTV comments. Comparing the Phases in Figure 3 for the NDTV data, there are notable differences in how various acts appear at different times. For example, during Phase 1 in NDTV data, notable peaks where differences from group means are above the significance level include challenging and denying acts – however, requests are also highly prevalent. For CTV comments, questions and statements and more positively inclined acts (acceptances and appreciations) are prevalent during early Phase 1, but denials and requests toward the end of Phase 1. We can find significant peaks in different acts at different points in time during the crisis. These are also different when comparing NDTV and CTV comments.

Table 3. Peaks in acts according to Phase and week in NDTV and CTV data.

Channel	Peaking acts		
	Phase 1, 2020	**Phase 2, 2021**	**Phase 3, 2021-22**
NDTV	challenges 17/02–24/02 requests 25/02–02/03 denials 25/02–02/03 statements 25/02–02/03	challenges 24/02–01/03 acceptances 01–07/03 apprec. 16–23/03 statements 17–24/04 denials 01–08/07 questions 01–08/07	questions 17–24/11,-21 apprec. 09–16/12,-21 acceptances 09–16/04,-22 requests 01–08/05,-22 acceptances 09–16/05,-22 statem. 25/05–01/06,-22 denials 25/05–01/06,-22
CTV	questions 01–8/02 acceptances 01–08/02 statements 09–16/02 apprec. 01–08/03 denials 01–08/05 denials 25/05–01/06 requests 25/05–01/06	denials 01–07/03 requests 25/04–01/05 requests 01–08/06 apprec. 17–25/06 challenges 01–08/07 acceptances 09–16/07	statements 01–08/11,-21 challenges 25/11–01/12,-21 questions 25/12–01/01,-22 apprec. 01–08/02,-22 apprec. 25/02–01/03,-22 denials 01–08/04,-22

To sum, our results indicate a positive answer to RQ1: there are significant differences in which acts comments to crisis news portray at different points in time during the crisis. The results also show notable differences when comparing NDTV and CTV datasets.

To answer RQ2, we analyzed whether the early crisis involved a discursive struggle. We consider discursive struggle to emerge through challenges (or accusations) and denials (e.g. of some information).

We see a peak in resolution-oriented requests in the NDTV news comments at the beginning of the Pandemic. There is also a peak in challenging acts, and denials, which is more in line with crisis theory. In CTV data, statements seem most prevalent in the early stages of Phase 1. Denials peak later, toward the end of the Phase. This indicates, concerning RQ1, that the beginning of the crisis produces somewhat of a different audience response than expected in classic crisis theory. It does not necessarily involve a significant amount of acts contributing to discursive struggle, but the audience may produce a significant amount of requests (or proposals) in response to the crisis – e.g. requesting authorities to act or otherwise aiming at crisis resolution. On the other hand, as seen in CTV data, (informative) statements about the crisis might be most common. Acts showing discursive struggle are also common in Phase 2 and Phase 3, which shows that several points in time during the crisis create discursive struggle over issues related to the crisis. In response to RQ2, our results show that audience responses to crisis differ somewhat from the classic theoretical view of how crisis discourses evolve during the early beginning phase of the crisis.

NDTV	Requests Jan-March/-20	Count	Challenges Jan-March/-20
805	should,you,demand,action	2064	is,it,virus,spread,not
302	virus,coronavirus	374	news,ndtv,channel,fake,media
85	china,send,him,chinese,yoga	260	you,stupid,idiot,fool,education
79	help,poor,can,people,food	199	she,teacher,be,why,mother
57	kerala,state,india	149	testing,cases,kits,symptoms
46	politics,you,party	140	india,indians,indian,people
43	god,pray,save,let,jesus	98	he,phfi,pm,guy
38	flights,international,all,airports	96	muslims,muslim,allah,islam
34	test,testing,negative,korea	91	god,spiritual,creator,garbage
30	stay,home,safe,guys,please,indoor	87	government,country,state,govt
27	tourist,ban,stop,traveling,karnataka	72	doctor,doctors,he,patients
25	mask,wear,n95,cover,surgical	70	die,selfish,parents,life,murder punish
CTV	**Questions Jan-March/-20**	**Count**	**Statements Jan-March/-20**
84	the,virus,china,we,this	161	trudeau,canada,canadians,is
71	canada,is,that,canadians	146	he,guy,him,this,is,was,like
65	this,why,video,who,high	128	doctors,medical,italy,thank
56	he,his,guy,this,does,what	114	lol,booshit,project,sadki,afieya
27	italy,doctor,would,treat,so,who	88	virus,coronavirus,china,corona
24	money,go,get,home,work,stay	75	masks,death,italy,pneumonia
24	lungs,be,you,with,smokers	68	too,late,little,ago,week,time
13	she,script,curious,write,adam	57	roxham,road,open,close,illegal
12	masks,mask,wearing,wear,why	48	she,just,did,fire,not,lad
-	-	46	my,asthma,temperature,cough oxygen
-	-	46	china,world,sg,now,government
-	-	42	home,pay,money,work,rent,food

Table 4. 12 most common topics in each of the first two peaking acts during Phase 1, NDTV above and CTV topics below.

To answer RQ3, we investigated if communicative acts could complement traditional topical analysis to offer deeper insights into crisis discourses. We approached this by separately investigating the topics of different notably peaking acts, analyzing how topics across acts differed during the two first significant peaks in acts during Phase 1, for both NDTV and CTV data (first and third peaks for CTV, as the second one included only two topics and 94 comments). The topic modeling results for these are presented in Table 4.

With a closer analysis of Phase 1, in NDTV comments (Table 4), requests are mostly related to requesting politicians and organizations to help (poor) people, proposing how to mitigate the situation e.g. by closing airports and banning travel, using masks and staying home. Challenges conveyed dissatisfaction with measures taken, or politicians and authorities (e.g. BJP i.e. Bharatiya Janata

Party), the media, or specific public figures (Kumar Singh) or other people, and claims about 'fake news', CTV topics, then again, included a lot of questions mostly about the virus and its effects on Canada, the situation in Italy, how the situation will affect work, how the virus affects people's lungs, and whether there is need to wear masks. Statements were most common and mostly related to opinions about the actions of politicians like Trudeau, how businesses would be affected by the Pandemic, how wearing masks helps, origin of the virus, how the virus might affect individuals with asthma, as well as opportunities to earn a living. To sum, topics prevalent for different acts and for the two channels differ notably: although there are some similar topics across acts (doctors, the media), their positioning was often different (appreciation of doctors vs. accusing doctors). The analysis of acts may thus provide more insights into the specific functions and purposes of comments – even ones that may have quite similar topics. Such an analysis can also reveal differences in prevalent topics across country contexts during the same period.

8 Discussion

We have shown in this paper that analyzing the acts of news comments can provide meaningful insights into crisis discourses on social media. We showed that there is significant variance in the use of specific acts along a crisis timeline. This can be highly interesting for social media monitoring during crises, indicating how the public is positioned to the crisis at a given time, and what concerns or questions they might have. This could help experts to anticipate what tactics might be needed for mitigating the crisis, or what problems might emerge in the near future. Such insights can also help reveal significant changes in the frequencies of manipulative or possibly problematic content (e.g. attacks against authorities). We showed that acts reveal more context for more fine-grained content analyses. This helps in analyzing what the purpose of comments is, which is crucial for understanding the meaning of comments and what they are about. Thus, the functions and purposes of acts are important in gaining a deeper understanding of how certain topics are talked about (e.g. politicians, doctors or the media) when analyzing large sets of social media data.

Few-shot learning models enable rapid deployment of applied models in novel settings, where often few resources are available and thus no large training datasets can be found for supervised modeling. This is very often the case for social media analyses during emerging events. The opportunity to rapidly develop novel models with few resources is crucial for crisis analytics. We have shown that it is possible to implement an applied model with new classes for empirical analysis, and to reach good performance even with a small manually annotated dataset. Acts such as challenges (and accusations) are interesting to study, especially to investigate discursive struggle related to the crisis, and we feel models including these should be developed further in future research.

One interesting finding in this paper is that although classic crisis research [41] stresses that discursive struggle occurs in the beginning of a crisis, we illustrated that the early public response to crisis is somewhat different as contrasted to the classic crisis theory [41]. Although classic crisis research on discursive struggle [41] has been conducted from the crisis management point-of-view, our results highlight the differences between these two, and how audience reactions might differ from how they are expected to react to crises. Public responses might notably emphasize resolution acts, rather than merely being thrown into a struggle of panic and chaos. Thus, audiences might also be a positive driving force in crisis mitigation. Discursive struggle also occurred during the mid-phase (Phase 2) and prolonged phase (Phase 3) of the crisis. Thus, crisis discourses during a long crisis might involve multiple points of discursive struggle – 'mini crises'.

8.1 Limitations

We acknowledge that perhaps other types of annotation procedures than what we have used might better represent the meanings of the comments in asynchronous conversations, e.g. their ambiguous nature, or multimodal and multilingual content. These could not be accounted for in this paper, but could be investigated in the future. Also, a comment with more than one act is counted more than once in the time series analysis, which might affect further analyses. The concept of discursive struggle, in addition, is a highly abstract concept. We did our best to represent the concept in our computational analysis, but it needs to be noted that our approach may be a limited interpretation of the concept.

As for ethical considerations and data privacy, we anonymized our data to not reveal the identities of participants in the comment section discussions. The data is stored on secure servers provided by Aalto University and handled with care. Our code, and an anonymized and de-identified version of our dataset and annotated data will be made available via application through our GitHub page. This is to ensure researcher use of the data but not to endanger the identification of individuals in the dataset.

9 Conclusions and future work

We have shown that our approach allows an analysis of how online discourses evolve during a crisis. Further research could investigate if similar developments in crisis discourses can be found in different cultural contexts, and in relation to different crises, also complementing computational modeling with qualitative methods. How to best annotate and model acts in asynchronous rapidly changing crisis conversations is still a developing area of work, e.g. to better represent multiple meanings of comments, multimodal and multilingual content. This research advances computational analysis methods for social media, elaborating how communicative acts can support analyses of the development of crisis discourses in large social media datasets. Such methods are needed for multi-faceted understandings of crises and social media engagement. Further, since social media is used as a venue for influencing public opinion and spreading disinformation, the discursive conflicts taking place in this arena are essential for e.g. crisis communicators, researchers, and journalists to both understand and manage. These insights will be increasingly important in pre-emptively mitigating disorder, confusion, and manipulation on social media during times of crisis.

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