Documenting Data Use in a Model of Pandemic "Emotional Contagion" Using the Rigour and Transparency Reporting Standard (RAT-RS)

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Abstract. This paper utilizes the recently developed Rigour and Transparency Reporting Standard as a framework for describing aspects of the use of data in an agent-based modelling (ABM) EmotiCon project studying emotional contagion during the COVID-19 pandemic. After briefly summarizing the role of the ABM in the wider EmotiCon project, we outline how we intend to utilize qualitative data from a natural language processing analysis of Twitter data and quantitative data from a nationally representative survey in model building. The presentation during the SSC 2021 will elaborate on the outcome of implementing the idea.

Keywords: Emotional contagion, COVID-19, social media analysis, natural language processing, agent-based modeling, artificial sociality.

1 Introduction

This paper, for the *Using qualitative data to inform behavioral rules* special track of the Social Simulation Conference 2021, describes plans for the use of Twitter content in the construction of an agent-based model (ABM) in the EmotiCon project studying emotional contagion during the COVID-19 pandemic. At the current stage, we describe an idea of informing an ABM with Twitter content and we cannot guarantee that, given possible obstacles in data processing and preparation, this idea will become reality. The conference presentation will report on the progress in implementation. Should we succeed, we would like to share and reflect on our process with conference participants. Should we fail, we would like to point to the obstacles we faced, and engage in a discourse of possible ways forward in using natural language processing (NLP) of Twitter content to inform ABMs. Either way, we look forward to discussing these issues with the broader ABM community.

The paper is organized as follows. In the next section, we briefly describe the Emotional contagion (EmotiCon) project. Subsequently, we use aspects of the Rigour and Transparency Reporting Standard [1] to outline the idea of how Twitter content can (hopefully) be used to inform the EmotiCon ABM. The RAT-RS consists of five question suites: a) model aim and context, b) conceptualization (what and why?), c) operationalization (how and why?), d) experimentation, and e) evaluation. We follow the authors' advice and fill in the RAT-RS during the modelling process (ibid., p. 13). Last, we share reflections on representativeness of Twitter content.

2 The Emotional Contagion (EmotiCon) Project

Computer modeling and simulation has been widely used during the pandemic to study and forecast the spread of COVID-19, contributing to the policy goal of "flattening the curve" of disease contagion so that they do not pass a threshold beyond which healthcare systems collapse due to lack of capacity to care for those who are infected and sick. In a similar way, the rapid spread of misinformation, stigma, and fear through "emotional contagion" [2] can pass a threshold beyond which other interpersonal and institutional systems necessary for social cohesion might collapse, leading (for example) to ideological polarization, culture wars, or psychological alienation and anxiety. Acknowledging existing ABMs of emotional contagion, including some based on social media analysis [3], [4], and extensive use of ABMs to study some of the possible causes and impacts of the COVID-19 pandemic [5], [6], the EmotiCon ABM we propose will bridge the two research trends, while utilizing a combination of insights from qualitative and quantitative data.

The EmotiCon ABM is developed with the support of Research Council of Norway funded project "Emotional Contagion: Predicting and Preventing the Spread of Misinformation, Stigma, and Fear during a Pandemic." The main goal of the EmotiCon project is to develop user-friendly multi-agent artificial intelligence tools that will enable Norwegian municipalities and other governmental agencies to (1) analyze and forecast the societal effects of their public health responses and social countermeasures to pandemics and (2) experiment with alternative intervention strategies for "flattening the curve" of psychologically and politically debilitating social contagion before trying them out in the real world. EmotiCon has collected Twitter content (via access to the twitter streaming API and new NLP techniques to analyze its content) and attitude data (via a representative panel survey) that will be used to specify, calibrate, and validate an artificial society (or "digital twin") of Norway. Simulation experiments will be designed to explore the psychological mechanisms and cultural factors that have shaped the societal reaction to the COVID-19 and to forecast the patterns in which individuals and communities are likely to understand and react to future pandemics.

3 Using data to inform the EmotiCon ABM

1. Model aim and context

1.2 What is the purpose of the model?

The main purpose of the ABM EmotiCon model is explanation - establishing a possible causal chain from a set-up to its consequences in terms of the mechanisms in a simulation [7].

1.3 What domain does the model research?
Attitude formation towards following local restrictions related to the COVID-19 pandemic.

1.4 What (research) question(s) is the model addressing?
If, and under what conditions, is the coherent causal mechanism of multidimensional (cognitive, affective and behavioural) attitude formation, as proposed in the agent-based model, able to elicit the patterns of declared compliance with **safety regulations** in the Norwegian population during the COVID-19 pandemic?

1.5 What is the MAIN driver for your initial model development step?
A selection of theories. These include identity fusion theory, moral foundations theory, reactance theory, cognitive dissonance theory, and emotional contagion theory. **Elements of those were previously implemented as ABMs (see Conceptualisation).**

1.6 Explain why this MAIN driver was chosen?
Because theories propose validated parts of the wider causal mechanism that can potentially be responsible for forming attitudes toward compliance with community-based rules of conduct.

1.7 What is the target system that this model reproduces?
The model represents a process of attitude formation among humans. The attitude in question has to do with willingness to following the local dugnad (that is, follow social distancing and other regulations or recommendations). In the beginning of the pandemic, the Norwegian government opted to use the word 'dugnad' to instil a sense of shared responsibility and solidarity in the Norwegian population. This wording was not chosen at random. Dugnad refers to an ancient old-Norse Viking era custom and means to participate in unpaid, voluntary, and often joint work efforts. In traditional Norwegian society this was a widespread form of collective self-help where neighbours and rural people joined forces to help each other tasks that were too demanding for the individual. Everyone helped out, and everyone got help. The modern variant of 'dugnad' most Norwegians will know from participating in helping the local football club, their children's kindergarten or doing the annual tidying up of the neighbourhood in the spring. Many Norwegians also spend a lot of their time each year doing work for various voluntary organisations under the heading of dugnad. Dugnad as a concept is still a strong part of the Norwegian identity and culture, and was in a national poll in 2004 awarded status as Norway's national word [8]. The Norwegian governments use of the word dugnad to mobilise the population to follow the guidelines has spurred some criticism since the burdens of the pandemic has not been equally shared. Certain groups in the society have taken most of the burdens of the Covid-19 measures: vulnerable children, lonely youths, individuals exposed to violence in their homes, the old and sick, those who lost their jobs, or those had to close their place of business. When the prime minister of Norway was fined for not following the guidelines herself in the winter of 2021, she gathered a larger group of people for a private dinner. We observe that

the governments use of the word dugnad has occurred less frequently when public officials have spoken publicly about new or revised measures.

The attitude towards dugnad is assumed to have three components: cognitive (representation of opinion about COVID-19), affective (emotions related to COVID-19) and behavioural (following restrictions of the local government). Humans share information via two channels: face to face and online. When communicating face to face, both the cognitive and the affective information that lead to following restrictions are shared. Cognitive dissonance mechanisms govern processing of received information, and emotional contagion mechanisms govern the rules for the diffusion of affective content. In online communication, cognitive content is processed in the same way, however the transmission of the affective state from the sender to the receiver is disrupted. Moreover, in face to face and online communication channels humans partake in different social networks. Real life networks are set up on the basis of socio-demographic homophily, but online communication networks are based on homophily and heterophily of opinions. As a result of decreased variance in online opinions that a human agrees with, online opinions bubbles are more homogenous than their real-life equivalents. On the basis of information and emotion diffusion, humans form their willingness to comply with local dugnad. There is no representation of natural environment in the model, however information (cognitive, affective and behavioural content of the attitude) is represented as a separate agent type.

1.8 Explain why this target system and these boundaries were chosen.

The EmotiCon project was funded as part of an emergency call from the Research Council of Norway in which researchers were invited to propose projects aimed at producing policy-relevant insights for the Norwegian government's response to COVID-19 and future pandemics.

2. Conceptualisation

2.1 What previous model is used (or models are used) as driver in this model? Give reference(s) to the model/models.

- The HUMAT socio-cognitive architecture [9];
- The Terror management model (TMM; anxiety theory, social identity theory, identity infusion theory; cit.). "Modeling Terror Management Theory" [10]
- "A Generative Model of Mutually Escalating Anxiety between Religious Groups" (MERV) [11]

2.2 Why is/are this/these previous model(s) used?

Those are models that have elements of relevant theoretical mechanisms that are relevant for attitude formation.

2.3 What are the elements of this/these previous model(s)?

HUMAT:

- cognitive content of information;
- cognitive dissonance mechanisms of adopting received information;
- mechanisms used by humans to estimate source persuasiveness;

Terror management model (TMM):

- Agents with characteristics such as religiosity (operationalized as tendency to believe in supernatural agents and participate in rituals that imaginatively engage them), tolerance for threats, and group identity.
- Terror management mechanisms for easing anxiety by participating in rituals

MERV:

- Agents similar to the ones in terror management model, but with interaction rules also informed by social identity theory and identity fusion theory as specified and integrated through the Information Identity System [12].
- Involved an adaptation of Epstein's Agent_Zero.

2.4 & 2.5 Describe how you moved from the previous model elements to the elements of your model & Explain why elements of the previous model were included, excluded or changed in the current model.

	EmotiCon element	Previous model element	Reason for inclusion
Agents	socio-cognitive architecture: cognitive dissonance in information processing	HUMAT	the need for representing cognitively motivated information exchange over social networks
	affect	TMM & MERV	the need to represent emotional contagion in social interactions
Interactions	socio-cognitive architecture: rules for information exchange (inquiring and signaling)	HUMAT	the need for representing cognitively motivated information exchange over social networks
	rules for assessing source persuasiveness (implementation of social identity theory & identity fusion theory)	MERV	the need to distinguishing different information processing depending of the information source (sources belonging to ingroup and outgroup of ego)

2.8 Describe the procedures and methods used to conceptualise the key target system elements as model elements. How did you make use of the evidence? What other sources did you utilise to conceptualise model elements?

EmotiCon has three major theoretical pillars: cognitive consistency theories; emotional contagion theory; and social identity & identity fusion theories.

Cognitive consistency theories are a group of theories that develop the concept originally described as cognitive dissonance by Leon Festinger. Dissonance between cognitions (or broader: cognitive inconsistency) is a motivational force for change in knowledge [13] or behaviour [14]. Dissonance reduction can be achieved in various ways [15]. Following an assumption from motivational intensity theory, the higher the motivation, the more effortful strategies can be implemented in the search of a better alternative [16], [17]. Therefore, that the higher the level of dissonance, the more effortful strategies agents can implement to resolve it [18]. Ex ante-strategies of EmotiCon agents to resolve cognitive dissonance, according to difficulty involve:

- distraction and forgetting;
- inquiring – collecting information from alters, which results in changing dissonant/consonant cognitions;
- signaling (in cases of social dilemmas) – trying to convince alters to ego's point of view.

Emotional contagion theory (ECT) was formulated and developed over the last few decades by Elaine Hatfield and colleagues [2], [19]. Our Norwegian surveys includes the "emotional contagion scale," developed and validated by Doherty [20], which has been translated and validated in several other contexts. The original hypotheses proposed and empirically tested in ECT deal with face-to-face contact between individuals, and its main postulated mechanisms have to do with mimicry, synchrony, and the effect of facial feedback on emotional experience [21]. Under certain conditions, people tend to "catch" the emotions of those with whom they are interacting. However, the concept of "emotional contagion" has also been adopted and adapted by several other studies of online interaction, focusing on the spread of emotion across online social networks (e.g., [22]–[24]. The fact that the original mechanisms of ECT cannot function in the same way in the spread of emotion on online (non-face-to-face) networks is sometimes glossed over in this literature. Given the differences in the mechanisms at work in these two kinds of interaction (offline and online), we plan to have the simulated agents in our ABM be situated within both types of network (guided by distinct behavioral and interaction rules). EmotiCon ABM also includes mechanisms informed by **social identity theory** (SIT) and **identity fusion theory** (IFT), both of which shed light on the ways in which a person's sense of identity can affect their motivation. SIT hypothesizes that individuals within different social groups attempt to differentiate themselves from each other as a results of pressures to evaluate their own group positively through in-group/out-group comparisons [25]. These value laden social differentiations can ratchet up tension between groups, which can impact people's motivation to protect their group. IFT postulates that motivation toward extreme behaviors is enhanced when a person's sense of their group becomes functionally equivalent to their sense of self [26]. Less fused individuals may have strong beliefs about how one "ought" to act (e.g., in defense of one's group) but highly fused people are more willing to actually engage in extreme behaviors in defense of the group (e.g., stigmatizing behaviors or sharing conspiracy theories related to the out-group). Our surveys included validated measures of both SIT and IFT, and we plan to include these as variables in our simulated agents.

3. Operationalization

3.1 & 3.2 What data element(s) did you include for implementing each key model element in the model's scope? & Are these data elements implemented with the help of qualitative or quantitative data or further models?

Agent characteristic at initiation	Used data	Data scale	Source
socio-demographic profiles	gender, age group, region of Norway	quantitative categorized	population statistics (consistent with the data used for computing weights for the EmotiCon surveys)
susceptibility to emotional contagion	scale of emotional contagion susceptibility	quantitative	EmotiCon surveys
COVID-19 related anxiety	single question	quantitative	EmotiCon surveys
identity fusion with the nation	single question	quantitative	EmotiCon surveys
willingness to follow dugnad	single question	quantitative	EmotiCon surveys
supported political party	single question	categorical	EmotiCon surveys
relevant motives for behaviour	Twitter content	qualitative	Social media analysis

3.3 Explain how data affected the way you implemented each model element and why.

Our choice of data elements was informed by our interest in modeling agent attitudes, behaviours and interactions in a way that simulated the spread of misinformation, anxiety, and stigma in the target reality (Norway).

3.4 What are the data elements used for in the modelling process: specification, calibration, validation, other?

Using data drawn from Twitter, we can address aspects of calibration of motives and networks. Given that the retweet, reply, and tagging data are available for every tweet in the Twitter database, we can map the interactions between individuals as an interaction network. This interaction network can be used to create a 1:1 initialization network for the ABM. Alternatively, parameters of this network, such as density, clustering, and average shortest path lengths can be used to parameterize larger, national-level networks as approximate starting points for the ABM. In addition, the Natural language Processing (NLP) data generated from analysis of the tweets can provide useful data for sub-model validation: specifically in validating patterns of online activity in diverse socio-demographic groups. The NLP and the survey analysis, along with subject matter expertise (SME) in social networks, emotional contagion, and public health communication, are being used for specifying the model elements and interactions. The calibration of the model will rely more on SME interpretation of the NLP. Will the simulated agents in the ABM behave as expected and will their interactions lead to plausible macro-level outcomes? The validation of the model will rely more on the survey data. Ideally, we will be able to validate simulation experiments by comparing them to the actual changes in the Norwegian population from October 2020 to April 2021.

3.5 Why for this use and not another one?
This data is easily available and the infrastructure for gathering the data existed prior to the pandemic, therefore, it represented a ready-made dataset that can not only address issues of network initialization and emotion, it also is a dynamic dataset that can be useful in validation and/or parameterization of the model in multiple stages of research.

3.6 Did required data exist?
Twitter: yes, however it needed preparation and analysis. **Survey:** primary data.

3.7 If it existed, did you use it?
Yes.

3.8 If you did not use it, why not?
All data that could be found quickly were used.

3.9 For the existing data you used, provide details (a description) about data sources, sampling strategy, sample size, and collection period. For the data you collected, provide details about how it was collected, sampling strategy, sample size, and collection period.

Twitter: From August to October 2020, we collected Twitter data using the Twitter streaming API with the following hashtags: "#koronaviruset", "#koronavirus", "#coronavirusnorge", "#karantene", "#koronaNorge", "#covid19norway", "#holdavstand", "covid19sweden", "#smittestopp", and "#coronakrisen". These hashtags are considered relevant for emotional contagion in Scandinavia in the wake of the COVID-19 pandemic. Due to the assumed linguistic uniqueness of the tweets (all being Scandinavian languages), we did not limit the API to any geographic region or language. The final data set comprised 26,727 unique tweets. All tweets that included at least one of the featured hashtags should have been returned by the API. All tweets returned by the API were included in the dataset. Upon review of the dataset, we found that there were non-Scandinavian languages that were utilizing similar hashtags and were also returned by the Twitter API. Because Twitter algorithms utilize hashtags and trending topics as key aspects to the newsfeed that are not limited by language (in fact some users already have access to automatic translation), we included all tweets scraped from the API that were found to include our target hashtags in our analysis. This is because it is possible for any of those tweets to have an effect on other users searching for their key hashtag.

Survey: The survey data was collected in collaboration with Kantar using their Gallup Panel. The panel consists of about 46,000 people who regularly respond to surveys. The Gallup Panel is put together for representativeness, and the goal is for the Gallup Panel to be a miniature Norway that reflects the entire country's population. In our survey 1200 people were interviewed in October-November 2020 and in April 2021. The margin of error (with full 50-50 distribution) is about +/- 2,8 %. The two data points gave us the opportunity to analyze the data longitudinally. The respondents had an unique ID number allowing us to track them. 763 respondents answered both surveys. The sample data was weighed using age, gender, and geography as weighing variables. The survey was developed using measures validated in previous research on the key dimensions in the survey such as anxiety, stigma, misinformation, conspiracy, personality traits, threat assessment, religiosity, and fusion index. In addition to this Kantar provided us with about 20 demographic variables from the Gallup Panel. A limitation of the survey is that it only reaches the part of the Norwegian population with access to the internet. In 2019 this is 98% of the adult population.

3.10 Justify your data collection decisions from 3.9.

The period of the pandemic, the duration of the project. While Twitter data is still being collected, the initial Twitter dataset was isolated between August and October 2020. This dating is largely arbitrary but it falls between periods of lockdowns and approvals of vaccines. As such we believe that it is justifiably representative of the COVID-19 conversation in our key area.

3.11 If you needed to analyse or transform/manipulate the data before including them in the model (regardless if you collected data yourself or you used existing data), what did you do and why did you choose this specific approach?

Twitter: Twitter data was analysed using ALAN Analytics' Pythia cultural-ontology (ALAN Analytics s.r.o, 2020). The Pythia platform combines advanced AI analytics with NLP to structure data in a way that is relevant to creating psychographic profiles of individuals in the dataset. This, in turn, allows for the creation of social digital twins. These digital twins can be further developed as multi-agent AI models to understand the rhetoric of online social networks. Pythia employs a unique term and phrase ontology that currently understands over 30,000 terms and phrases and works in over 40 languages. It rates texts based on their prevalence or relationship to over 50 different socio-cultural and psychological dimensions and can create personality and moral profiles based on unstructured text data. Tweets were analysed for moral dimensions, as well as their readability, biological themes, and gender and temporal focus, users are also profiled based on their Big-5 personality (or "OCEAN") factors. Tweets were also subjected to classifier systems trained to detect misinformation about COVID-19, threats, and hate speech. The output of the analysis is the probability that an individual will view the tweet as misinformation or hate speech, and the probability that the individual is currently experiencing high or low levels of social, predation, natural, or contagion threats. In addition, we also created an "engagement score" for each tweet, which is the sum of the tweet's favourites, replies, and retweets (the three primary actions for engaging with information on the social network).

Survey: Either no or minimal data preparation was needed.

4 Conclusion and Next Steps

Using Twitter contents in agent-based model building has been increasing in popularity. For a number of agent-based models Twitter is the represented target system [27]. Other models [28], just like ours, acknowledge that online tools (e.g., Twitter) are indeed important communication channels that provide individuals with opportunities to exchange information alongside other, perhaps more traditional, channels (e.g., face-to-face interactions, newspapers). Irrespective of whether Twitter reality is the whole or a part of the target system, major concerns regarding representativeness of Twitter contents remain when the data is used in informing agent-based models. In this section, we would like to reflect on two specific types of representativeness, i.e., how well a Twitter analysis represents (1) the investigated topic and (2) the communication on Twitter on that topic.

The most common technique for sampling tweets is the topic-based approach [29] used also in our study. In such hashtag-centred studies, representativeness of tweets for the investigated topic depends on the choice of search terms that are tracked by the API user, on the one hand, and the popularity of those hashtags with relation to all other Twitter content, on the other. In reality, both are difficult to estimate. Validity of the search terms depends on the existence and early identification of widely-adopted hashtags. Given the thematic context of our study (i.e., the SARS-COV-19 pandemic), the implemented research design and urgency to collect relevant data that otherwise would be lost (esp. the fact that Twitter data collection was executed before the agent-based model was conceptualized), we decided to select a broad scope of COVID-19 related hashtags. Only some of those hashtags directly referenced the local measures against the spread of the pandemic (physically distancing and quarantining). In the time period between August and October 2020, all of our chosen hashtags might have been sufficient to represent the topic of following dugnad. As the pandemic evolved, and the local measures changed, the choice of search terms should be adjusted to maintain the sensitivity of these indicators. Popularity of the hashtags has a complex relationship with thematic representativeness. On the one hand, popularity of the hashtags indicates validity. In a perfect world where unlimited, free access to Twitter for scientific purposes was granted, it would be possible to collect the entire population of tweets containing a hashtag. In the world we live in, probably for justifiable reasons, access to Twitter content is limited by the Twitter API to a maximum of 1% of the total current Twitter volume. Therefore, when search terms are very popular, Twitter API returns a non-exhaustive sample of tweets. In practice, this necessitates a limit in the number of selected hashtags and selection of only the most relevant for the investigated topic.

Hashtag-centred tweet collection raises even more serious concerns with respect to representativeness for Twitter communication. Hashtags represent a self-selection of tweets (and users). Therefore, the collected data is missing out on an unknown volume of content which may relate to the same issues, but does not contain any relevant text markers [30]. Random sample of tweets with the use of Streaming API is a viable alternative to hashtag-centered sampling. Even though it is free of self-selection bias, it faces other significant limitations [29]. For the time being, hashtag-centric studies seem to be better suited for tracking changes over time.

The last reflection we wanted to make has to do with our experience using the RAT-RS standard to report the use of data in the ABM. Overall, we found the standard intuitive and easy to use. It is important to highlight that we used the standard at the stage of model conceptualization, when our data was already collected but not yet analysed. In other words, we knew what data we had, but did not yet know what information it carried. Our ambition was to incorporate the knowledge we had about available data into model conceptualization alongside the theoretical assumptions guiding the model mechanics. In this particular context, data availability considered early in the process posed constraints to ideas for concept development. We treated RAT-RS as a tool that gave us a good overview of where certain elements could fit in. We had the experience of zooming out and identifying the role of larger chunks of a puzzle in a more harmonious whole. This is particularly useful in a relatively complex model such as ours. However, once the data is analyzed, more detailed and method-tailored descriptions will be necessary to aid in effective communication and replicability.

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