Emotional Contagion in Scandinavia during the COVID-19 Public Health Crisis

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Abstract

In this article we present the findings of social media analysis of the spread of misinformation in the wake of the COVID-19 pandemic and outline how analyses of the psychological properties of a text can be used to optimize strategic messaging online. Our data used Twitter data, collected during the COVID-19 pandemic and analyzed using a suite of AI based analytical tools, which provided data for further empirical analysis. The analysis yielded insights related to the differences in the dynamics of the spread of misinformation within (and outside of) Scandinavian countries. Analysing this data enabled us to explore three hypotheses: (1) Misinformation will be associated with specific moral signatures, which will differ between Scandinavian and non-Scandinavian samples, (2) Levels of engagement will be associated with specific themes and moral concerns, which will differ between Scandinavian and non-Scandinavian samples, and (3) Within Scandinavia, similar unique signatures will be discernible at the country level, with Sweden driving significant differences. These specific results provide guidance for healthcare professionals responsible for communicating information and crafting messages that are more resonant with their target population and more generally demonstrate the ability for social media analysis to be useful in strategic decision making when going beyond focusing on engagement metrics or sentiment alone.

Keywords

Covid-19, misinformation, social media, moral foundations, natural language processing

Background

International audiences sometimes perceive the Nordic countries as somewhat homogeneous in terms of culture, social structure, and political systems of governance. This is why many observers found it surprising that there was such a discrepancy in the responses of these countries to the Covid-19 pandemic (and in the resultant death rates). Sweden is clearly an outlier with 787 deaths per 1 million population (as of December 2020), which is 4-5 to ten times higher than its neighbouring countries (Claeson & Hanson, 2021). Several explanations have been offered for this anomaly, including the idea that female heads of state are better equipped to handle large scale crisis situations; after all, Sweden was the only Nordic country with a male head of state during the first year of the pandemic (Barse, 2020). But there are likely more broadly sociological explanations for the differences. Generally, the literature comparing the Nordic countries paints a picture of an east–west polarization, where Denmark and Norway are characterized as exhibiting more liberalistic traits than Finland and Sweden, which offer a more organic, and in the case of Finland, even communitarian traits (Normann, Johnsen, Knudsen, Vasström, & Johnsen, 2017; Rokkan, 1987; Todd, 1996).

This article sheds light on these differences, and makes suggestions for public health communication, based on theoretically informed social media analyses carried out within and across Nordic countries (and around the world) during fall of 2020. How are healthcare professionals responsible for communicating information about the pandemic supposed to make sense of these differences and craft messages that promote healthy attitudes and behaviours in the public? The two main theories shaping the empirical analysis and recommendations are emotional contagion theory and moral foundations theory, both of which are explained below.

Indeed, the Nordic countries did take very different approaches to the pandemic. While Sweden has remained open, the other countries have chosen shutdowns of varying degrees and durations. On 2020 March 12, Norway introduced the most restrictive measures in peacetime, while Sweden opted for a 'liberal' approach free from 'draconian' measures (Sefton, Sandvik, & Jumbert, 2020). Sefton et al. offer four possible explanations for Sweden's outlier status. A first hypothesis has to do with national differences in the experience of crises. Sweden has not experienced a terror onslaught such as Norway did on 22. July 2011 and mostly escaped the crises of WW2. A second explanation has to do with the relationship between politics and bureaucracy. In the Norwegian system, each minister is directly responsible for the underlying management of their department. The Swedish system, on the other hand, is based on a clear distinction between politics and the operationalization of politics. Moreover, unlike Norway, most of the government ministries in Sweden are small and most of the state's activities are carried out by large government agencies that have a high degree of autonomy.

Third, the differences could be explained by the different management models adopted by the Nordic countries. Since the 1990s, Sweden has privatised the welfare sector to a greater extent than the others. More privatisation and cost pressures on municipalities resulted in increased intake of unskilled labour and more short-term employment using substitutes. The use of substitutes and unskilled workers in the elderly and care sector in Sweden could be a factor in the higher rates of death among the elderly compared to the other Nordic countries. Fourth, Sweden's outlier status might be due to differences among countries in the relationships between the people and the governments. The red thread in Sweden's public health communication was "trust" – the people should trust the expertise of the government and its agencies and the government would trust the people of Sweden to use their common sense. In Norway, however, the government's approach was to use words as "dugnad" and focus on that we are in this together and mobilise a sense of solidarity. Norwegian Prime Minister Solberg said at the time: "This is not the time for me, this is the time for us." The difference in the two styles of communication builds on different societal configurative ideologies and history. The word "dugnad" means to take responsibility not only for yourself but for your family, your neighbour, and your community.

"Emotional contagion" refers to the theory, first developed by Hatfield and colleagues, which argues that emotions can be "caught" as people relate to each other socially (Hatfield, Bensman, Thornton, & Rapson, 2014; Hatfield, Cacioppo, & Rapson, 1993). Just as there is a need to flatten the curve of the spread of COVID-19, so is there a need to flatten the curve of rising anxiety, stigma, and misinformation related to the disease. The use social media analysis to study online emotional contagion has been growing rapidly in recent years and new tools for studying the phenomena have been developed and improved (Coviello et al., 2014; Goldenberg & Gross, 2020; Hill, Rand, Nowak, & Christakis, 2010). Because of its prevalence, the social media platform Twitter is often used in such studies (Fabrega & Paredes, 2013; Ferrara & Yang, 2015; Xiong et al., 2018). Since the beginning of the COVID-19 pandemic, Twitter has also been utilized to study the spread of misinformation about the disease (Huang & Carley, 2020; Shahi, Dirkson, & Majchrzak, 2020). Our social media analysis will also utilize Twitter data and study the spread of anxiety, stigma and misinformation, as explained in the Methods section below.

Moral Foundations Theory (MFT) postulates the existence of (at least) five evolutionarily grounded intuitive "foundations" for morality (Haidt, 2007; Haidt & Joseph, 2004). Three of these – ingroup/loyalty, authority/respect, and purity/sanctity are commonly referred to as binding foundations because of the way in which they facilitate the cohesion of social coalitions. The remaining two – fairness/reciprocity and harm/care – are commonly referred to as individualizing foundations because of their apparent connection to the emphasis within the liberal philosophical tradition on the welfare and rights of individuals. Research on the moral foundations has consistently found that while liberals tend to rely primarily on individualizing foundations, conservatives are more likely to rely on all five foundations. This reveals various combinations of preferred intuitive foundations or "moral signatures" (J. Graham, Haidt, & Nosek, 2009). Recent survey questionnaire research has shown that the moral foundations predict social distancing defiance in the wake of the pandemic in the US (A. Graham et al., 2020).

As we will see below, this is relevant for our study because of the different "signatures" between Scandinavian and non-Scandinavian tweets, especially in relation to authority, purity, and fairness. Understanding how these signatures, and the variation in modes of engagement, influence emotional contagion related to misinformation and anxiety related Tweets in Scandinavia can inform public health officials' planning and evaluation of policies to "flatten the curve" of misinformation and emotion. Social media is clearly affecting people's values as emotional contagion spreads online, for good or bad (Steinert, 2020). Fighting misinformation about COVID-19 on social media will require careful analysis and planning of intervention strategies (Pennycook, McPhetres, Zhang, Lu, & Rand, 2020), that can also be useful in other scenarios. This will become increasingly important for public policy because moral foundations profiles also appear to influence willingness to accept vaccination (Rossen, Hurlstone, Dunlop, & Lawrence, 2019), and because the presence of pathogens could accelerate political authoritarian developments that are already polarizing contemporary societies (Murray, Schaller, & Suedfeld, 2013). Lastly, we hypothesize that there will also be significant differences between the nations within Scandinavia, regarding the content of information circulating on twitter, with Sweden being the most likely outlier due to its unique approach in handling the pandemic response.

Methods

From August to October 2020, we collected Twitter data that contained selected hashtags considered relevant for emotional contagion in Scandinavia in the wake of the COVID-19 pandemic. The final data set was comprised of n = 26,727 unique tweets, each of which had at least one of the following hashtags: "#koronaviruset", "#koronavirus", "#coronavirusnorge", "#karantene", "#koronaNorge", "#covid19norway", "#holdavstand", "covid19sweden", "#smittestopp", and "#coronakrisen".

This Twitter data was analysed using CulturePulse's Pythia platform (CulturePulse, Inc., 2022), which utilizes an advanced AI analytics platform combining natural language processing (NLP) and a form of social digital twins called multi-agent AI to better understand the rhetoric of online social networks. Pythia employs a unique term and phrase ontology that can understand over 30,000 terms and phrases and works in over 40 languages. It can rate 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. For this analysis, tweets were analysed for moral dimensions, as well as their readability, biological themes, and gender and temporal focus. For each variable, there is a dictionary of key terms and phrases which are associated with that dimension. This method is known as the word count (or term frequency) method and is often employed in social media analysis using older dictionaries with fewer terms; the dictionaries used for this analysis were revised to mitigate biases known to exist in western psychological research. For example, in earlier dictionaries for the LIWC program, which also uses word frequency analysis, the categories for religiosity and morality are highly focused on Christian conceptions of the subject and therefore are problematic for cross-cultural research (Pennebaker, Booth, & Francis, 2007).

Our current analysis employed dictionaries that extended these domains to include more cross-cultural relevance. In analysing these dimensions, we focused on the moral domains of harm, fairness, authority, ingroup loyalty, and purity (J. Graham et al., 2009). For each moral domain, there are virtue and vice categories, indicating whether the terms associated with that domain suggest that an individual is referring to the domain as a virtue or a vice. For the other dimensions, word lists were built and validated during previous cross-cultural research to assess the viability of NLP system to create social digital twins of social groups (Lane, 2018, 2019, 2021);

examples of the analysis can be found in the *online supplemental materials*.[1] The categories we analysed are included in Table 1 along with some examples of the kinds of concepts that would indicate each category in our analysis.

Tweets were also subjected to several classifier systems, trained to detect misinformation about COVID-19, threats, and hate speech. In these systems, each tweet is analysed, and 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. Further documentation of these systems is provided in the online supplemental materials.

Table 1: Categories and examples of concepts that are coded for that category

Category	Description
Authority Vice	“refuse”; “disobey”
Authority Virtue	“revere”; “honor”
Fairness Vice	“dishonest”;
Fairness Virtue	“honest”
Harm Vice	“harmful”; “kill”
Harm Virtue	“safe”; “shield”
Purity Vice	“sin”; “prostitute”
Purity Virtue	“Pristine”; “abstain”
Ingroup Vice	“abandoned”
Ingroup Virtue	“fellowship”
Eating Drinking	“fruit”; “food”;
Sex	“foreplay”
Body	“flesh”; “saliva”
Health	“thermometer”; “fever”; “virus”

In addition to analysing the tweets for their personal, cultural, and psychological themes and properties, 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). Our analysis assumes, for the sake of simplicity, that an individual is tweeting in the language native to their respective country. Therefore, tweets that were written in Scandinavian languages were tagged in our dataset so that we can investigate differences between Scandinavian and non-Scandinavian tweets.

[1] https://github.com/culturepulse/emoticon

Using the Pythia platform, tweets from the selected hashtag were gathered via the Twitter API. All tweets that included at least one of the featured hashtags were included in the dataset. Upon review of the dataset, we found that there were other languages outside of Scandinavia that were utilizing similar hashtags and those were included in the dataset. 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 https://blog.twitter.com/pt_br/topics/product/2019/sua-pagina-inicial-seu-idioma.html), 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 (a profile of the tweets is included in the Results section).

Our main goal in this exploratory analysis was to test the following hypotheses. H1: Misinformation will be associated with specific moral signatures, which will differ between Scandinavian and non-Scandinavian samples. H2: Levels of engagement will be associated with specific themes and moral concerns, which will differ between Scandinavian and non-Scandinavian samples. H3: Within Scandinavia, similar unique signatures will be discernible at the country level, with Sweden driving significant differences.

Results

The tweets in our data set (*n* = 26,727) had an average engagement score (the sum of the tweets favourites, replies, and retweets) of 32.82 (*sd*=102.7) with the most engaging tweet having 2,989 engagements (the median was 2). This is not unusual in social media data, where engagements, followers, and other aspects of the network typically display power law distributions that suggest scale-free structures (Arnaboldi, Passarella, Conti, & Dunbar, 2015; Dunbar, Arnaboldi, Conti, & Passarella, 2015; Gonçalves, Perra, & Vespignani, 2011).

The scraped data included tweets in the following languages: Turkish (*n* = 13,240), Finnish (*n* = 5,370), Norwegian (*n* = 907), Czech (*n* = 894), English (*n* = 623), Hungarian (*n* = 315), Swedish (*n* = 267), and Polish (*n* = 130). All other tweets came from another language with less than 100 tweets or were part of a group of tweets where the language could not be determined (typically this is because it includes little text and only utilizes graphics or emoticons). Data from tweets written in Scandinavian languages was coded as "Scandinavian" and all other tweets were coded as "non-Scandinavian." The range of languages found in our dataset is interesting in itself insofar as it suggests that hashtags are shared cross-linguistically, outside of Scandinavian languages. As hashtags are an important part of how Twitter's algorithm decides what is to be shown to a user, the prevalence of such a wide variety of languages, from less socio-politically stable regions like Poland, Turkey, and Hungary, suggests that there may be an outsized, and outside, influence of emotionally charged political rhetoric from those areas. However, this is beyond the scope of the current paper and will be analysed in future research. Due to the non-normality of the data, non-parametric statistics were employed to see if significant differences existed between the data drawn from Scandinavian vs non-Scandinavian tweets. Analyses of the data using Mann-Whitney U tests revealed several significant differences between Scandinavian and non-Scandinavian tweets.

First, we found that Scandinavian tweets were more likely than non-Scandinavian tweets to be considered as misinformation (W = 52526269, $p < 0.01$). However, the mean score of the likelihood of a tweet being misinformation in the Scandinavian sample is less than 50% (45.7%), and the median likelihood of the same is 55.4%, suggesting that although there is a statistically significant difference, its impact is negligible. As such, while there is a statistically significant result here, we feel the need to clarify that this statistical significance is not likely to be a critical policy relevant finding for stakeholders, as the distribution of misinformation attributions and tweet engagement is generally quite low (see online supplemental material).

Due to these differences found on key variables between Scandinavian and non-Scandinavian tweets, independent regressions were created for analysing our hypotheses. Upon exploring a standard linear regression, it was observed that the regression did not meet the standard assumptions. Therefore, robust linear regression models, which are appropriate when the statistical assumptions of a typical linear regression are violated, were utilized with 95% confidence Intervals, which can allow for more robust and reliable tests of the effects of different variables.

To test whether misinformation was associated by specific moral signatures, we ran a robust linear model, the results of which are included in Table 2.

Moral Domains Regression Results

	Dependent variable:	
	misinformation	
	(1)	(2)
Authority Vice	-0.979***	-3.339***
	(0.325)	(0.645)
Authority Virtue	0.432***	-0.464***
	(0.103)	(0.151)
Fairness Vice	1.354	2.168**
	(0.970)	(1.088)
Fairness Virtue	0.965**	1.175*
	(0.436)	(0.637)
Harm Vice	-0.011	0.271
	(0.128)	(0.276)
Harm Virtue	0.290*	0.855***
	(0.165)	(0.218)
Ingroup Vice	5.436***	5.703***
	(0.844)	(2.185)
Ingroup Virtue	-0.534***	-0.368*
	(0.134)	(0.224)
Purity Vice	0.877***	0.044
	(0.127)	(0.245)
Purity Virtue	0.899**	2.930***
	(0.373)	(0.533)
Morality General	2.152***	0.463**
	(0.135)	(0.205)
Note:		*p<0.1; **p<0.05; ***p<0.01

Regarding misinformation, violations of authority are negatively associated with misinformation, but promotion of authority morality is positively associated with misinformation outside of Scandinavia and negatively associated with it in Scandinavia. Similarly, fairness virtues are positively associated with misinformation in Scandinavia, outside of Scandinavia fairness vice is positively associated with misinformation. In addition, while purity virtues are positively associated with misinformation in both regions, purity vice is only associated with misinformation outside of Scandinavia. Ingroup vice was also found to be significantly related to misinformation ratings in both areas, but ingroup virtues are only related to misinformation outside of Scandinavia. Harm virtue and morality generally were positively correlated in both groups, while harm vice was not significant in either group.

Following from this, we aimed to better understand what factors are associated with engagement of COVID related tweets in our corpus. We performed an additional two regression models with engagement as the dependent variable, and the other key themes and measures included in the regression for exploratory purposes.

Engagement Regression Results

	Dependent variable:	
	Engagement Count	
	(1)	(2)
Readability (LIX)	0.233**	-0.840***
	(0.044, 0.421)	(-0.921, -0.758)
Misinformation	-2.118	-5.371**
	(-10.708, 6.473)	(-9.618, -1.124)
Eating/Drinking	6.976	-331.325***
	(-194.116, 208.069)	(-423.411, -239.240)
Sexual language	-166.423*	-307.852***
	(-353.427, 20.580)	(-384.918, -230.787)
Corporeal Language	-249.196***	46.766
	(-433.026, -65.367)	(-31.997, 125.530)
General Biology	375.930***	280.930***
	(186.128, 565.733)	(198.259, 363.600)
Health Concerns	-72.752	-346.052***
	(-259.380, 113.876)	(-431.373, -260.730)
Female Gender Focus	337.591***	-1.658
	(271.741, 403.441)	(-37.570, 34.254)
Male Gender Focus	52.839	-38.167***
	(-12.003, 117.681)	(-65.956, -10.377)
Focus Past	38.498	6.816
	(-17.055, 94.050)	(-23.251, 36.884)
Focus Present	64.199***	15.238**
	(34.652, 93.746)	(0.958, 29.518)
Focus Future	62.834	-16.264
	(-35.694, 161.362)	(-69.480, 36.951)
logSigma	5.097***	3.915***
	(5.083, 5.111)	(3.894, 3.935)
Constant	-59.458***	53.991***
	(-72.705, -46.211)	(47.897, 60.086)
Observations	17,000	6,620
Log Likelihood	-74,276.650	-26,178.400
Akaike Inf. Crit.	148,581.300	52,384.810
Bayesian Inf. Crit.	148,689.700	52,479.980
Note:		*p<0.1; **p<0.05; ***p<0.01

The coefficients and their 95% confidence intervals can be found in Table 3. Temporal Focus Future was removed from the final model as it was not significant.

Our analysis of engagement suggests that readability had a negative relationship with engagement in Scandinavian tweets. Tweets of a sexual nature were found to have a negative effect on engagement. Also, both personal finance and personal leisure topics were found to have a positive effect on engagement with Scandinavian tweets. It was also found that sociality, positive sentiment, and anger had negative effects inside Scandinavia, while affect had a significant positive effect inside Scandinavia.

Finally, we aimed to see whether there were also significant differences between the different countries within Scandinavia. If so, there might be additional cultural differences that should be considered by the specific ministries when dealing with how COVID is addressed and discussed within their respective online communities. While we did not find significant country-level differences on the rating of misinformation, we did find significant differences between countries on anxiety, with a post-hoc test showing that the key difference was between Norwegian (mean = .004) and Finnish (mean = .01) samples (95%CI=[-0.004, -0.001]; p < .01). We also found a significant difference in the prevalence of affect between the countries, with post-hoc tests revealing significant difference between Norway (*mean* = .106) and Finland (*mean* = .094) (95%CI=[.005,.018], p <.01), Sweden (*mean* = .076) and Finland (95%CI=[-.03,-.007], p <.01), and Sweden and Norway (95%CI=[-.043,-.018], p <.01).

The data shows a significant difference in engagement count with COVID tweets between the different countries, led by a very high average engagement with tweets in Norwegian (mean = 50.62) compared with Danish (mean = 1.45, 95%CI[36.4,61.95], p < .01), Finnish (mean = 12.24, 95%CI[35.54,42.41], p < .01), and Swedish (mean = 16.25, 95%CI[-41.82, -26.92], p < .01). There was also a significant difference between Swedish and Danish (95%CI[0.90, 28.71], p = .03), likely due to the longer tailed power law distribution of values observed in the Swedish data. Here it is interesting to note the more beta-distribution-like shape of the data in comparison with the more power-law distributions of the other countries (all graphs are included in *online supplemental material*).

This same trend in engagement was also reflected in the use of moral language by each country, where again significant differences were found and post-hoc tests revealed that these differences were significant between Norwegian (mean = .017) and Danish (mean = .009, 95%CI[.002, .013], $p < .01$), Norwegian and Finnish (.005, 95%CI[.009, .013], $p < .01$), and Swedish (.006) and Norwegian (95%CI[-.014, -.007], $p < .01$).

Discussion

The results above reveal several interesting differences in online social media engagement regarding COVID, misinformation, and affect in the Scandinavian and non-Scandinavian tweets.

In addition to the statistical results found in the analysis (further discussion is included in the supplemental materials), it is useful to note that this information helps policy makers to engage more directly with online audiences by providing a profile for information that can best engage their target audience. In the case of COVID-19, one key issue has been the spread of misinformation online, leading to individual decisions that can have negative impact on health and communities as those who are utilizing misinformation endanger others by spreading the virus. Using the information provided here, health officials can craft messages with reliable, scientifically sound information that is presented in ways that are most digestible to those who are engaging with (or susceptible to) misinformation, making it more likely that reliable information about the pandemic can be integrated into the worldview of those who might put others at risk.

These results suggest that there are specific cognitive and information signatures that are unique to the Scandinavian cultural context. That is to say, what is likely to work to combat misinformation in Scandinavia is not as likely to work (and in some cases might exacerbate the effects) in other areas outside of the region (and vice versa).

In particular, the signatures found in the data suggest that in Scandinavia policy makers are more likely to be successful in communicating with misinformation engaging users if their messages do not emphasize authority, but rather stress fairness and violations of purity while also promoting ingroup values.

Furthermore, our results found that engagement and moral language related to COVID can vary between countries within Scandinavia. The data suggest that a Scandinavian approach in general can be useful, but that any campaigns to combat misinformation, or create engaging factual information on social media, should be attenuated to its appropriate context. For example, in Sweden, tweets were relatively low in anxiety when compared with other countries, suggesting that emotional or reactionary tweets are not going to be well fit with the Swedish Twittersphere. Therefore, the largely emotionally charged reactions of many on social media in response to Sweden's herd immunity approach were unlikely to have penetrated or spread as widely in Swedish social media as they would have locally; relegating such information to tweets that might signal support for a policy or engage in “virtue signalling” within a country, but would have little effect in Swedish social media. To be compatible with the Swedish social media culture, the tweet should be relatively unemotional, and relatively low in moral language (similar to Finish levels), but higher focus on leisure and financial subjects would likely benefit a messages success in Sweden. As such, health officials in areas aiming to impact Swedish social media audiences should focus on clear, not-dumbed-down discussions on the virus’ impact on leisure and finance, and steer away from emotional manipulation in order to “sell” the tweet.

Overall, our results suggest that to increase engagement, health professionals could produce information that focuses on personal finance and leisure, but steers away from themes of anger. However, the findings on readability suggest that presenting this in a complex way might be more useful for integration with misinformation. This may be due to a tendency toward conspiratorial thinking, whereby engaging with the information and reflection on the information (as one would when learning a new worldview or conspiracy) may be one way of increasing reflection and consolidating information into the memory of the individual reading and engaging with the information. The idea is that although the information is not misinformation, the information has the structure of misinformation and therefore is more cognitively compatible to those who are prone to accept misinformation or have already build up cognitive schemas based on misinformation. In this way people who believe in misinformation will accept the new information because it is following a cognitive path of least resistance to be integrated to their cognitive schema (see table 2 for data on the relationships between properties of tweets and misinformation). Generally, our study also shows that within Scandinavia, the Norwegian population was engaging most with COVID-related tweets, and that they also had a higher prevalence of moral language generally in tweets related to COVID, whereas Swedish and Finnish tweets had lower prevalence of moral language.

To summarize, using online social media analysis to create a framework for effectively combating the spread of misinformation and the promotion of health policy information, we found that there is no one-size-fits all approach. Some content will work well in Scandinavia and poorly in other regions, while other content will work poorly in Scandinavia, but outperform outside the region. Specifically, different emotional and moral signatures can have opposite effects and experts and policy makers should be careful when making public statements to make sure that there are optimal effects.

Naturally, there are also limitations to this approach. The most popular social media site in Scandinavia (Facebook) is increasingly limiting researchers’ access to data. This is why we limited our analysis to Twitter, which is very open in its ability for researchers to gather data. Future research will need to reach out to other online social media platforms (e.g., Reddit). Moreover, our online analysis should be complemented with off-line data; our team has already begun replicating these observed effects using a nationally representative survey sample in Norway. Lastly, this data, which is fully digitized and also can be used to form a viable social network, can also be investigated using more advanced techniques, such as agent-based models and multi-agent artificial intelligence systems (Lane, 2013, 2021; Lane & Shults, 2018).

Future research, which can combine online social media, survey, and computational modelling could contribute to understanding and even predicting trends in beliefs in conspiracies, misinformation, and even religion (Lane, 2021), thereby creating an experimental platform that health care professionals could use to "test" their messages about the pandemic before trying them out in the real world.

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