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ORIGINAL ARTICLE

Examining the relationship between COVID-19 and suicide in media coverage through Natural Language Processing analysis

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Abstract
Background and objectives: Suicide is a major public health concern, media can influence its awareness, contagion, and prevention. In this study, we evaluated the relationship between the COVID-19 pandemic and suicide in media coverage through Natural Language Processing analysis (NPL).
Methods: To study how suicide is depicted in news media, Artificial Intelligence and Big Data techniques were used to analyze news and tweets, to extract or classify the topic to which they belonged.
Results: A granger causality analysis showed with significant *p*-value that an increase in *covid* news at the beginning of the pandemic explains a later rise in suicide-related news. An analysis

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based on correlation and structural causal models show a strong relationship between the appearance of subjects "health" and "covid", and also between "covid" and "suicide".
Conclusions: Our analysis also uncovers that the inclusion of suicide-related news in the category health has grown since the outbreak of the pandemic. The COVID-19 pandemic has posed an inflection point in the way suicide-related news are reported. Our study found that the increased media attention on suicide during the COVID-19 pandemic may indicate rising social awareness of suicide and mental health, which could lead to the development of new prevention tools.

Introduction

Suicide is a major public health issue around the world, being the second cause of death in young people (especially those under 24 years old).[1−3] Despite the worrisome data, effective preventing measures are still lacking.[4]

Novel prevention strategies that are currently being utilized take advantage of recent developments in Artificial Intelligence (AI) and its applications.[5,6] AI and more specifically, Machine Learning (ML), are capable of analyzing enormous amounts of data which raises the accuracy of risk detection.[7] At a basic level, algorithms can identify the main topic of a text, predict the risk and develop prevention guidance. Natural Language Processing (NLP) is technique commonly used in ML[8] that technique commonly used in ML (Chapman et al., 2011) that tries to extract information and process the structure and meaning of non-tabular text data for tasks such as topic modeling, natural language understanding, natural language generation, syntactic parsing, and others.

News media are key to understanding how society and the general population react to topics.[9] Not only does the news media cover current events, but also generate opinions and possible action towards them. The influence of media in suicide has already been studied utilizing AI an ML techniques.[10,11] Also, these applications are being tested as a way for preventing suicide.[5,7] The relationship of suicide-related news with other different topics has previously been studied, with discouraging results (see[10] where the authors found a negative impact of suicide-related news). There, we found that suicide was more linked with the topics of *Islamism, politics* and *culture* than with the tag *health*. Interestingly, the inclusion of the topic of *health* gained influence during the COVID-19 pandemic, where there is an increase in news related to health problems and mental health consequences of the pandemic and the strategies for its control.[12]

Many newspapers are also active in social media, where news and information are globally shared. Furthermore, social media are utilized worldwide to express personal updates, attitudes and emotions.[13,14] Suicidal thoughts and ideation are also commonly conveyed on this kind of platforms.[15,16] In particular, Twitter has been found to be influential on people's attitudes towards health topics and health information, such as women's health,[14] psychotherapy,[17] and Mediterranean diet.[18] Specifically, the relationship between Twitter posts and suicide have previously been studied, with interesting results.[13,15,16,19−22] Additionally, Twitter users have shown increasing interest in mental disorders, with suicide being on of the main topic of interest in this field.[23]

To the date, this is the first work that analyzes the impact of COVID-19 in the news media coverage of suicide utilizing Big Data an ML techniques.[24] In this study, we focus on assessing the content and topic classification of the news about suicide and its evolution during and in the aftermath of the COVID-19 pandemic. We pose the hypothesis that the rise in health topics' attention related to the COVID-19 pandemic[4] has put mental health issues front and center.[25] In addition, we extract the causal relation between extracted topics (i.e., tags). Finding the relationship (it terms causality or rather associativity) in topics is important because it reveals out the way in which suicide is covered in the news media.

Material and methods

Web scraping

The key tool applied in this study is the Big Data technique called web scraping (also called web crawling or mining) to extract an immense amount of texts (20Mil tweets and 100K news). In particular, this technique gets a group of servers querying massive quantities of data from public web pages on the internet. We deployed a network of cloud servers and a local server to break up the load of the work:

(i) A Mongodb database server: a no-sql database widely used in Big Data projects in order to store large amounts of data.

(ii) A cloud server (scraper): this server contains our software coded with the NodeJS programming language. This software searches the web archive of the newspapers and the different twitter accounts, then the nodes save the data in the Mongodb database.

(iii) A local server: A server with scripts coded in NodeJS and Python searches our Mongodb database and trains the ML models to classify the subjects in the news and tweets. Then, this server analyzes the full database and calculates by modeling the probability that each item has of covering the subject of suicide.

The previous process gives us two datasets:

- **A newspaper news dataset**: We extracted 100K news from American and British newspapers (from CNN, the Guardian UK, the Guardian US, the New York Times, The Sun US, The Sun UK, L.A. Times and USA Today) from

January 2020 to April 2021. These newspapers were chosen because they are some of the most read international news sources available through the Internet and written in the English language.
- **A tweet news dataset:** We also extracted 20Mil tweets from the 100 main news twitter accounts, which include the previous newspaper web pages. These tweets were published from January 2019 to April 2022. Twitter was the social media platform chosen for this study because of the tweets' accessibility.

In newspaper media, every piece of news is classified by tags. This tag or keyword helps describe the text and allows it to be found again by browsing or classification (we used common tags for all the newspapers, such as *justice, economy, politics, international, technology, health,...*).

The goal was to classify news articles and tweets as either being about suicide or COVID. We therefore extracted over a million tweets with the hashtags: *#suicide, #suicided, #selfharm, #teensuicide* and *#covid, #corona, #covid19, #coronavirus, #pandemic, #lockdown*.

This corpus of data conformed by newspaper news and Twitter news on one hand and sucide and covid tweets on the other, allowed us to develop the following three ML models:

- **Multilabel Subject Classification Model**: Using the full corpus of tagged news we trained a ML model using Naive Bayes (NB) Multilabel classification. This model takes a text input in the English language and returns a set of tags such as *justice, economy, politics, international, technology, health... (11 categories in total)* with their probabilities
- **Suicide Subject Classification Model**: Using the suicide hashtags we trained a ML model using NB for long text classification (such as news) and SVM for short text classification (such as tweets and headlines). This model takes an input text (if the text is short it uses NB, in another case it uses SVM) and outputs a number between 0 and 1 that represents the likelihood that text has of covering the subject of suicide.
- **Covid Subject Classification Model**: Using the covid hashtags we trained a ML model using NB for long text classification (such as news) and SVM for short text classification (such as tweets and headlines). As in the previously described model, this model takes an input text (if the text is short it uses NB, in another case it uses SVM) and outputs a number between 0 and 1 that represents the likelihood that text has of covering the subject of *covid*.

The models were trained using the python package scikit-learn. Feature extraction was achieved by applying a n-gram vectorizer to the texts. In order to train suicide and covid subject models we used a dataset of hashtags involving those subjects, whereas the multilabel subject dataset was trained using the tags provided by the newspaper news metadata. We applied SVM for short text and NB for longer texts because this combination returned the best results in terms of precision, recall and F1 score. Table 1 summarizes the metrics of the models obtained:

Table 1 ML metrics of the models trained for news classification. The precision is the ratio tp / (tp + fp) where tp is the number of true positives and fp the number of false positives. The recall is the ratio tp / (tp + fn) where fn is the number of false negatives. The F1 score can be interpreted as a harmonic mean of the precision and recall, where an F1 score reaches its best value at 1 and worst score at 0.

Model	Precision	Recall	FI-score
Suicide subject classification model	1	1	1
Covid subject classification model	0.99	0.99	0.99
Multilabel Subject Classification Model	0.78	0.71	0.73

The data extraction and analysis process is detailed in Fig. 1.

The scraping method carried out in our study (cloud servers (i), (ii) and (iii)) has already been used (with variations) by the authors successfully.[11,26] In[11] the authors apply a similar method to study the impact of suicide news to suicide cases. In[26] the authors also study the impact of gender violence news in a similar manner.

Causal graphs

Causal graphs, also known as causal diagrams or directed acyclic graphs or, are graphical representations of causal relationships between variables. They are used in many fields, including epidemiology,[27] economics[28] or psychology,[29] to understand and model the relationships between variables and to make predictions about future outcomes.

In a causal graph, variables are represented as nodes, and causal relationships between variables are represented as directed edges or arrows. The direction of the arrow indicates the direction of causality. For example, if we have variables A and B, and A causes B, then there will be an arrow pointing from A to B in the graph. If there is no causal relationship between two variables, they are not connected by an arrow.

Since our dataset consists of a high number of tagged news media items, causal graphs are a useful tool to understand the connections between the different tags. To calculate causal graphs we used the NOTEARS structure learning algorithm.[30,31]

Results

Temporal fluctuations in suicide and COVID awareness

In order to understand the temporal fluctuations of the presence of news (tweets and newspaper) regarding COVID and suicide, we used our *covid subject classification* and our *suicide subject classification* models to analyze our datasets described before.

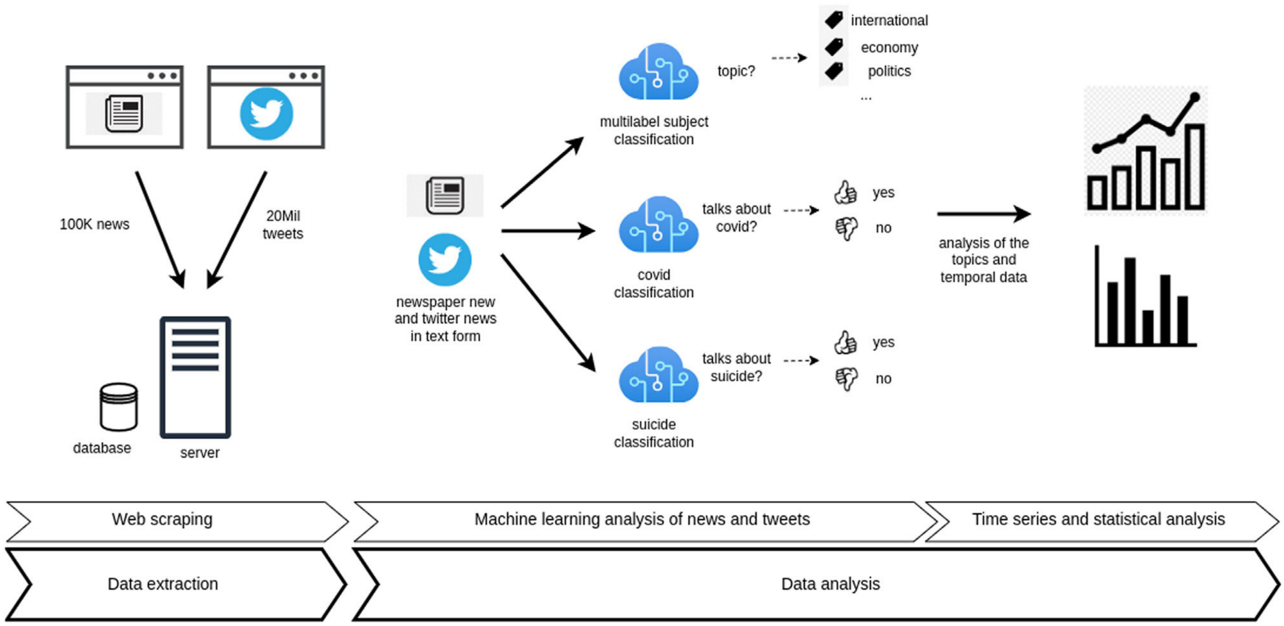

Figure 1 Data extraction and analysis.

This process consists in running the model on each news article and tweet to obtain two probabilities: the probability of the presence of the *suicide* subject and the probability of the *covid* subject in a given piece. After obtaining these probabilities we took all the news corresponding to each day and calculated the average daily probability to obtain a measurement of how much the news spoke about *suicide* or *covid*. Figs. 2 and 3 show the temporal plot of these two daily average probabilities for newspaper news and Twitter news, respectively

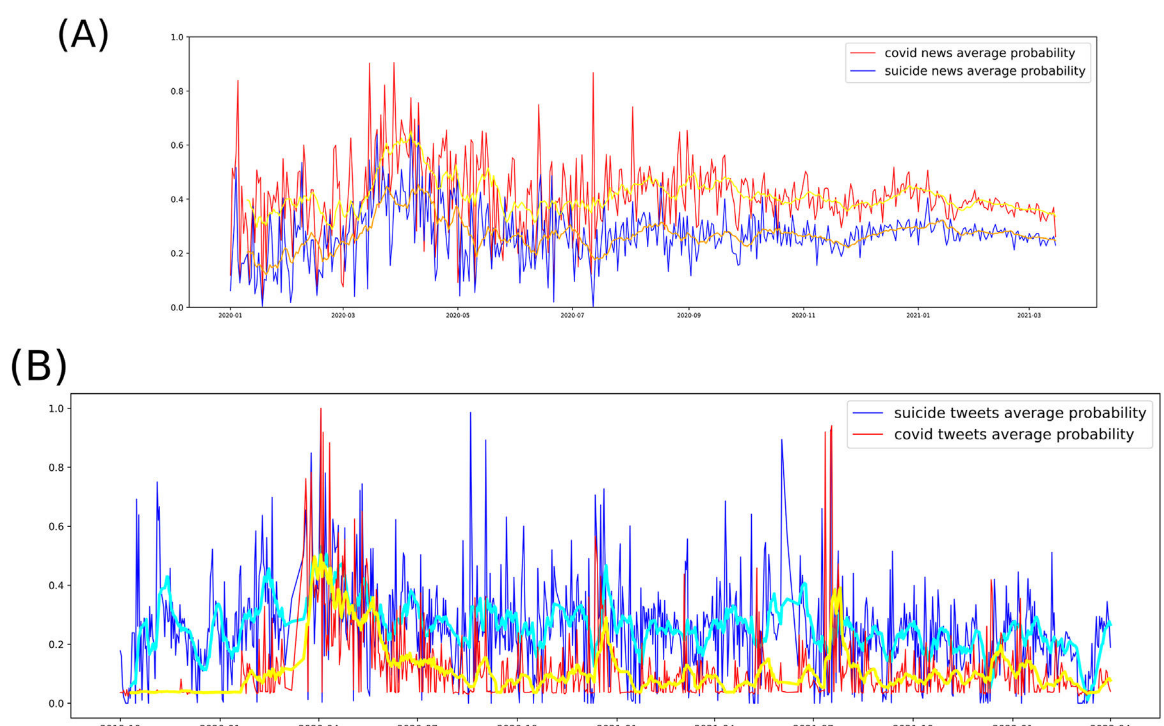

Figure 2 First plot (A) shows *suicide* and *covid* average probabilities for newspaper news. The second (B) shows the corresponding plot for Twitter news. In red we have the suicide subject average probability. In blue we have the covid subject average probability. The yellow and orange curves show the moving average (10 days) to visualize the trend of the covid and suicide time series, respectively. The graphs were obtained by calculating the average daily suicide subject probability (blue) and the average daily covid subject probability (red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

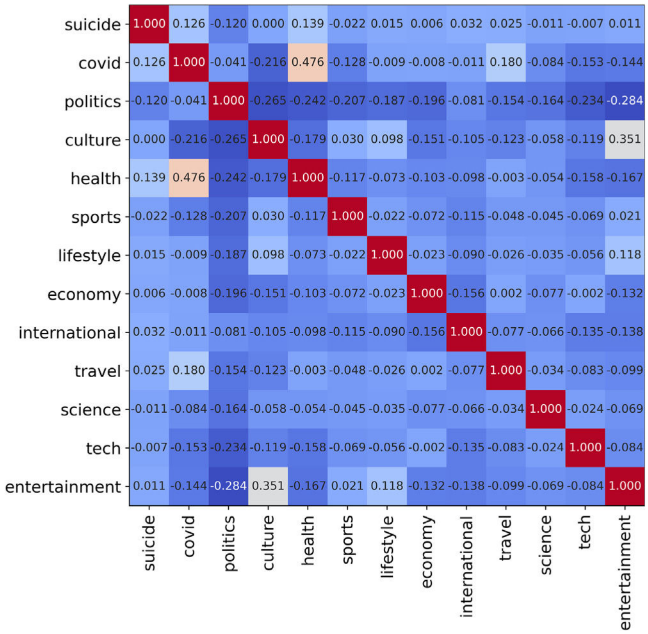

Figure 3 Correlation matrix of all Twitter news from the beginning of the pandemic (a similar matrix was obtained using the newspaper news). We included all the probabilities from the multilabel subject model and the probability of suicide and covid obtained with the other two models. Each number represents the correlation between the two variables (row and column) colored by significance. The matrix was obtained by calculating all subject probabilities and then computing each correlation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

In Fig. 2, we clearly appreciate that the two time series (covid subject average probability and suicide subject average probability) behave very similarly. We see how the covid subject average probability starts to rise at the beginning of the pandemic (February 2020), which could explain a similar rise in the suicide subject average probability.

To confirm this observation, we compared the stationary part of both time series and applied a Granger Causality test, obtaining that **the stationary component of the covid subject average probability Granger-causes the stationary component of the suicide average probabily** (p-value < 0.05 with lags 2 to 12 for tweets series, and p-value < 0.05 with lags 6 to 12 for news series) . **This means that an increase of covid average probability explains an increase of suicide average probability.**

Thematic complexity of news during the pandemic

Once established the existing connection between the rise covid-19 news and the rise of suicide-related news, we want to understand the thematic interconnection between this two topics.

We carried out a complete analysis of the full corpus of news during the pandemic (using the three models). Fig. 3 shows the correlation matrix of each subject probability. There is a relatively high correlation (0.476) between covid probability and health probability. Similarly, there is also a mild correlation between suicide and health probability (0.139), although not so high. This does not contradict our previous finding since the Granger causality analysis uses the temporal fluctuations in these two subjects.

We can also see a relatively high correlation between travel and covid (0.18).

This gives us an insight about the way these subjects (health, covid, suicide and travel) are related to each other.

To complete this analysis, we used casual graphs to explore how the presence of *covid* probability can be explained from the rest of the probabilities. This analysis can help to understand conditional dependencies between variables.

Fig. 4 (A and B) shows the result of the NOTEARS structure learning algorithm.[30,31] This method consists in a very optimized algorithm for learning bayesian networks based on continuous optimization for structure learning. To obtain the graphs (A) and (B) we applied the NOTEARS algorithm over the categorized tweets and news of the dataset during the first three months of the pandemic. After comparing the resulting causal graphs produced by the algorithm we found out that the subgraph (C) was the most common one when focusing on the relationship of suicide-related news with the rest of the categories.

In a structural causal model like the one in Fig. 4, each node represents a variable and each arrow conveys causal relation between variables in that direction. Focusing on the covid and suicide nodes of the graphs, we can see that the subgraph (C) of Fig. 4 appears in both previous graphs (A) and (B) for tweet news and newspaper news.

This subgraph points out that the covid subject probability can be explained with travel, health and suicide subject probability. In combination with the correlation analysis, **we can say that an interpretation of this is that each time covid subject is present (high covid probability), it is accompanied by travel, suicide or health subject.**

The connection between health, suicide and covid is very clear since health and suicide are clearly intertwined. Although it could appear surprising, the connection between covid and travel can be explained by the travel bans during the lockdowns and other mobility restrictions. A preoccupation in the news regarding this restrictions may explain how it is thematically and causaly connected with mental health and suicide.

Notice that although there is a connection from suicide to covid this does not contradict the Granger causality analysis (wich shows that high covid subject values precede suicide subject values), since this connection should be understood as a variable association rather than true causality.

Thematic evolution of Covid and suicide-related news

From the full dataset of news (newspaper or Twitter news) we extracted those referring only about COVID or suicide. We did this by selecting those that had a high suicide subject probability (more than 0.9 using our *suicide subject classification model*) or by selecting those that had a high covid subject probability (more than 0.9 using our *covid subject classification model*).

Using our *multilabel subject classification model* we studied the subjects present in the suicide and covid news in

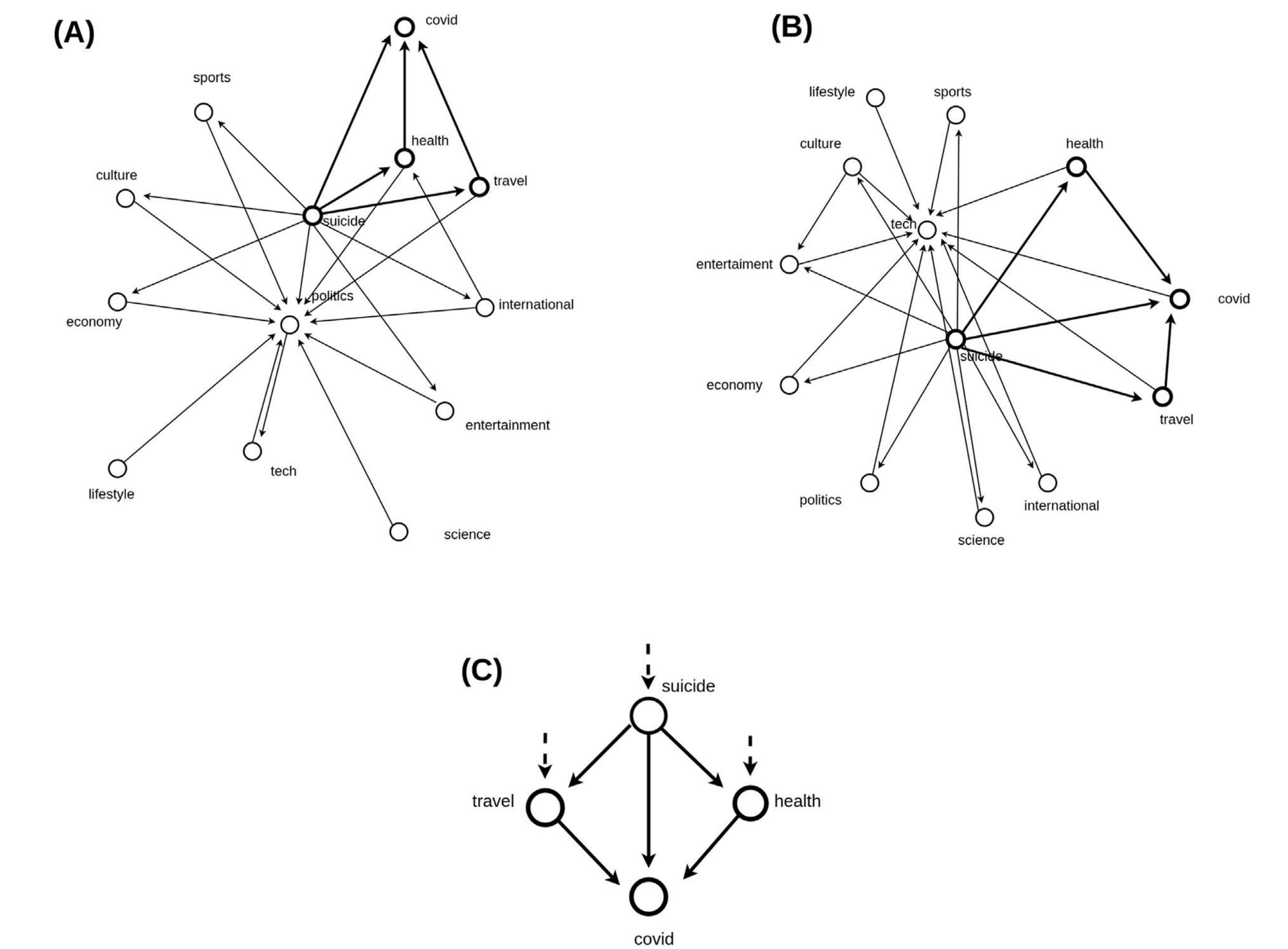

Figure 4 Structural Causal Graph of the full dataset of news during the pandemic first three months (A, B) (for computational reasons, similar graphs were obtained the following months). On the left we see the graph corresponding to Twitter news, and on the right, to newspaper news. Graphs A and B were obtained using the NOTEARS algorithm, each arrow represents a causal relationship or association between nodes. (C) subgraph represents suicide and covid nodes in Twitter and newspaper news. Notice that covid subject probability is caused by travel and health, also suicide causes health and travel probability. Notice that we are using the term "causes" in the sense of causal models, not as definitive causality.

order to compare them. The mosaic plots depicted in Fig. 5 confirm the results obtained with the causal graphs.

The first two plots of Fig. 5 show the predominance of the thematic *health* in suicide-related tweet news. Note how the health thematic increases at the beginning of the pandemic in suicide-related news. By looking at the second two plots of Fig. 5, we appreciate that the main thematics for covid tweet news are health and travel (followed by politics and international) and that during the first months of the pandemic there are proportionally more travel news than in the following months.

The strong presence of health and travel subjects for covid and suicide-related news underline the results obtained in the previous section.

Discussion

Many factors have been studied to have an impact on suicidal ideation, and among them contagion effect (in family, in celebrities and in press) has been a topic of interest for years.[32] On this issue, media covering of suicide has been studied to be influential, not only in a negative way but also (and more recently studied) it can have a protective effect.[33,34] Harmful influence on the reporting of suicide in media is known as Werther effect and it worsens with the content and the way suicide death is depicted.[35—38] On the contrary, Papageno effect is a protective effect on suicidal behavior determined by overcoming facts on suicide and empathetic responses to people suffering suicidal ideation.[32,34,39—41]

Based on this hypothetical protective effect and in order to prevent contagion, the WHO (World Health Organization) developed guidelines and recommendations for the news media professionals to ameliorate the elaboration of news on suicide[42] supported by other associations dedicated to suicide prevention.[42—45] This strategy is applied to the general population, where few strategies have been proven effective.[46,47] On general lines, journalists should avoid explaining and detailing suicidal methods and should focus on the possibility to get help and overcome the suicidal crisis, with the aim to educate the population in mental health

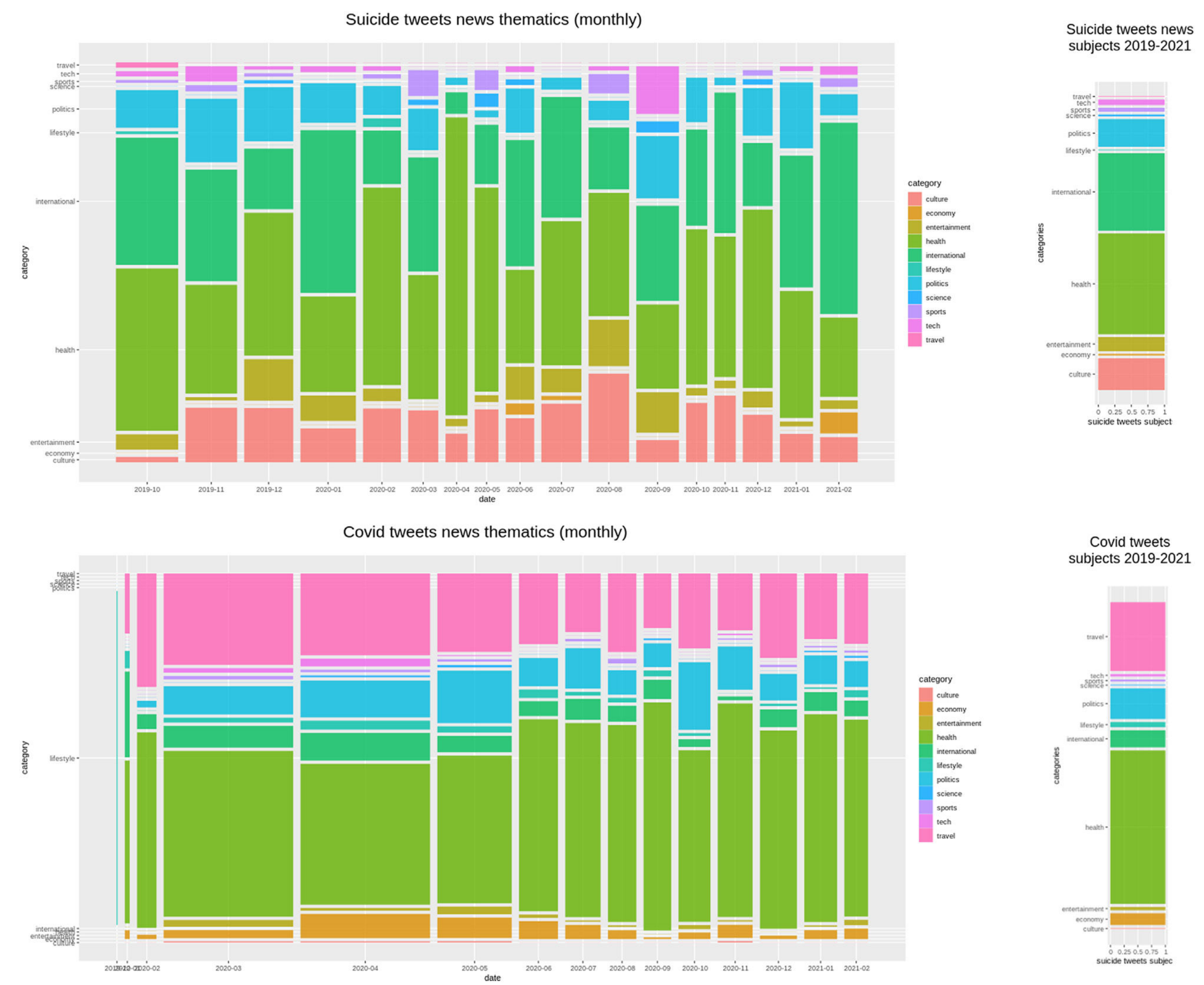

Figure 5 These figures show four mosaic plots of the evolution of thematics (culture, economy, entertainment, health, international, lifestyle, politics, science, sports, tech and travel) in the different periods (monthly and yearly). A thicker section represents a proportionally larger amount of news about that subject, colors represent the different subjects or thematics. The graphs were obtained determining the proportion of news in each subject for every month studied from 2019—10 to 2021—02. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

issues.[45] The adherence to the WHO recommendations is considered by some the principal factor related to the negative effect in suicidal behavior.[48,49]

On the other hand, the use of Internet and social media, for the purpose of spreading health information and health-related content, can be of great utility in the field of suicide prevention.[50] This type of medical research know as *infodemiology*[51] has been studied to be helpful to study changes and trends in public health and health policies.[17] Social media content is commonly utilized by infodemiology researches to explore attitudes towards health problems in a population.[14,17,18] Infodemiology can pose many interesting applications in the prevention of suicidal behavior, given the immediacy of information dissemination. What is more, suicide has been found to be one of the most commonly health subjects (global and mental health) referred to in Twitter.[23] Thus, the use of Internet, social media and infodemiology can also have interest in the elaboration of evidence-based guides and protocols and its importance can only grow.

The way suicide is depicted in news media has previously been studied utilizing Big Data an ML techniques.[10,11] It has been found that suicide-related news were classified in many topics, though its inclusion as health news was anecdotal until the COVID-19 pandemic. This crisis might represent a trigger for the awareness of mental health problems and their report.[12,52] There is agreement between mental health professionals that the pandemic would have long-term effects in mental health that may include a growth in the number of deaths by suicide.[53,54] Actually, a growth in the number of suicide attempts has already been found in the United States of America.[55] With this in mind, it will be necessary to maximize precautions in the reporting of suicide-related news by the news media.[56,57]

The news media have been reporting massively about COVID since the breakout of the pandemic. From the correlation and causal analysis we deduce that the tag covid is clearly associated with the terms health and travel. Although it can seem surprising, the link between covid and travel can be explained by the news related to travel restrictions and lockdown during the pandemic. The analysis also shows an association between covid and suicide is emerging though not so strong.

The time series analysis shows that, as the news about covid swell, also do the news about suicide. This is significant by Granger causality, and there are many factors that can explain this rise apart from journalism awareness about suicide (for example, rising in number of suicide attempts as a mental health consequence of the pandemic, interest in publishing sensationalist events... [52]). Otherwise, it is positive that suicide takes its spot in the news media. More importantly, suicide is increasingly more linked with health than it has been before. This tendency can be observed at the beginning of the pandemic, and it seems to be maintained. Furthermore, the health topic is predominant in suicide-related news during this period, just opposite of what was observed in our previous study.[10]

It is essential that the connotations of suicide change, still the news media should check adherence to the reporting guidelines[42] in order to promote suicide prevention and convey about solutions or help (Papageno effect).[34]

Study limitations

Many suicide deaths do not appear in the suicide media, and those that do, tend to have a sensationalist connotation or are about famous people. This weakens our observational protocol and the big data approach. Nevertheless, this bias may not interfere in the topic classification of the news.

Future lines of research

The influence of media in suicide has been already studied utilizing AI and ML techniques.[10,11] Our study shows a strength in the ML and NLP application: the suicide topic extraction of the media articles and the definition of a suicide subject probability for each piece of news. This suicide subject probability technique proved especially fruitful when we used it to map all news within a period, which pinpoints several events that pushed both the increase in news regarding this subject and public awareness, though we have not focus on the impact in the number of suicide deaths.

It is vital to promote adherence to the reporting guidelines and to raise awareness about suicide in general population because this might help to diminish the number of people dying by suicide each year. How to improve this social consciousness about suicide may be one research line to continue. Moreover, using Big data techniques to deepen the understanding of the quality of the suicide report would enable novel strategies.

Conclusions

Our results show a palpable connection between the high reporting of covid news and the high reporting of suicide-related news during the months of the pandemic. We show that high values of covid news precede high values of suicide-related news. Our results point that there is a temporal predominance of health subjects in news regarding suicide during the pandemic.On the other hand, our causal analysis explore the connections between these two topics, showing that the media commonly links suicide and covid through the subjects travel and health. The fact that suicide had been reported more often and in connection with mental health is very uplifting since suicide is the second cause of death in young people worldwide.[10] News media could have an impact on the promotion of mental health issues, which may be supported by social media.[58] On this line, we believe the COVID-19 pandemic has posed an inflection point.

It is encouraging to observe that the trends of reporting suicide might be evolving. Hence, news media would help raise awareness on the problem that suicide represents, and thus, promote resources to find help.[2,42] With time, news media would play an even more important role on suicide prevention. Because there is no health without mental health.

Code availability

The code used for this paper is available at the github project: https://github.com/news-scrapers.

Ethical considerations

For this work, no additional permission or informed consent were needed.

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Declaration of Competing Interest

The authors declare no conflict of interests for the elaboration of this work.

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