Analysing mobile apps that emerged to fight the COVID-19 crisis

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Executive summary

COVID-19 emerged as a pandemic and lead to a multi-faceted global crisis. Among others, it triggered the collection and integration of data – not only about infections and their distribution but also about human behaviour. At the same time, we witnessed the diverse and quickly emerging use of old and new digital tools. The work presented in this technical report focusses on a subset of such tools: mobile applications (apps). It is part of our work on the digital transformation of governance, including also implications on the provision, access and use of information. The technical work described here is intended as a baseline for follow-up scientific publications on the topic.

With the goal to improve our understanding about the emergence and evolution of COVID-19 related apps, we decided to consider three prominent sources of information: Google Play and the Apple App Store; Twitter; and the JRC's European Media Monitor (EMM). Each of the three channels is processed separately, but we occasionally benefit from interconnections. The app stores are our primary information sources, in the sense that we retrieve app descriptions from them on a regular basis (using a defined set of search terms). We retrieve relevant information automatically and then carry out a manual analysis of the most relevant apps in more detail. The scraping of Twitter applies pre-selected hashtags and terms, but it is also used to filter particularly interesting apps. The high amount of data (tweets) received allows for an exploratory approach to find patterns and clusters of messages or users. In the case of EMM, we primarily use the news that are again collected for a predefined set of search terms, on an occasional basis to find relevant news entries for a given app.

This report presents the technical details of our multi-channel approach to the monitoring and analysis of COVID-19-related mobile apps. It includes and builds on the following results:

- Information about mobile apps that was retrieved from the stores and enriched by a manual analysis. In total, we analysed 837 app descriptions that were retrieved between 20/04/2020 and 02/08/2020.

- Tweets about COVID-19 that were collected since March 15th, 2020. In total, we collected more than 233 million tweets until 12/11/2020.

- 4442 articles that we collected through the EMM for a period of approximately seven months (between 07/04/2020 and 12/11/2020).

In a nutshell, we can take away some early findings about the technology we used, the methodology we applied, and also the content that we analysed.

The early findings from the technical work can be summarized as follows:

- Both the APIs that we used to retrieve data from the app stores have some limitations, for example, in the number of requests that are allowed, the change of the behaviour during the many months we used them, or the need to launch additional requests in order to receive all the descriptive attributes that we were interested in (e.g. information about privacy policies and access permissions requested by each app). Still, after obtaining the descriptive information about the apps from both stores, it requires substantial manual work in order to identify which apps are provided in both stores.

- The tweet analysis and the resulting hashtag networks have given us some visual clues of relations among topics related to COVID-19 mobile apps. The subsequent sentiment analysis has shown that the relevant debates were polarised (there was strong sentiment polarity). It also showed us that there was much more attention in countries who faced hard the COVID-19 crisis (such as Italy, with the Italian contact tracing app attracting the highest attention in Twitter among the EU contact tracing apps, and the Norwegian one being the least mentioned

one). Not surprisingly, most of the tweets for each app were in the official language of the country covered by it. This introduces some bias in sentiment analysis, since the sentiment analysis libraries available for each language are different.

- Monitoring media through the EMM provides a useful tool for understanding the propagation of information on apps. Reusing a controlled list of keywords which is across channels (e.g. for social and traditional media outlets) allows for comparison of the information. A shortcoming of such an approach is the bias of the resultant information introduced by the languages that are used.

Early findings from the methodology that we applied:

- It is useful to combine information from different information channels, and the exercise that we initiated opens multiple avenues for further exploring COVID-19 related apps, and their evolution over time. We focussed our work and decided to concentrate in baseline research.

- Results from automatic (objective) processes can be combined with the findings of manual (subjective) work. However, to harmonise results coming from different viewpoints and approaches, we rely on cross-checking (peer reviews) of analysis results by more than one researcher. Also, numerous meetings to discuss the definition of the attributes while the analysis is ongoing is a crucial factor.

- The manual analysis with many people is both a strength and a challenge of the approach we followed for the manual analysis of the mobile applications on the app stores. We must acknowledge the shortcomings of using attributes with a subjective dimension.

- It is challenging to define attributes, and app categories in a fluid context, new features and functionalities were emerging while we were in the process of analysis the apps. Also, the actual meaning of which app is interesting at a given moment in time changes, for example, contact tracing apps caught our attention in the early phase and until the summer 2020, whereas we found emerging apps to deal with recovery scenarios more interesting over time.

Early findings from the analysis of COVID-19 related apps:

- As the first case of COVID-19 cases started in China in early December 2019, followed by the first cases in Europe in the second half of January 2020, and declaring the global health emergency on 30th January 2020, the actual emergence of COVID-19 related apps accelerated in April 2020.

- The COVID-19 crisis led to the development of many different apps, much more than the contact tracing apps that are prominently present in the news and on social media. We now have a rich landscape of COVID-19 related apps available, and they are highly diverse across countries. Different clusters of functionalities can be spotted, but multiple practices emerge in terms of addressing quarantine management, mobility, etc.

- The public sector, i.e. local, regional and national governments, is by far the main provider of COVID-19-related apps (although most of the times these apps were formally developed by companies contracted by government).

- Sharing of personal data seems often not regulated by clear privacy policies, especially for apps released in countries outside the EU. This was indicated when analysing the text provided in the app description but would need to be verified by installing and checking/completing the attributes from a user experience perspective.

- Almost each country, especially in the EU, adopted its own contact-tracing app. Most of these apps are based on the Bluetooth technology to exchange data in a fully anonymous and privacy-respectful way. High initial interest was observed across the multiple channels which decreases over time (which means a communication campaign is critical).

- The geographic distribution of offers is highly diverse, some countries (such as India, Brazil and the USA) provide a high number of apps, but also provide different apps with similar functionalities for different cities or regions. We did not spot this general trend in European countries.

- The functionalities that the COVID-19 apps provide change over time. Whereas many apps focussed on information provision about regional situations and training (e.g. how to wash hands) early on, we whiteness a peak of contract tracing apps over the summer of 2020, followed by an increase of apps that support re-entering to schools, work, or online records of test results. Logically, the countries that were hit earlier by the crisis undergo this evolution earlier – as compared to those which were affected later.

In addition to the lessons that we already learned, we see several opportunities to build on our initial findings and to gather more scientific knowledge about emerging solutions, their impact, and their differences.

In the short term, we intend to extract more descriptives from the current dataset – including examples, such as, graphs about the involvement of a health authority, the presence of a clear privacy policy, etc. Also, a deeper analysis might be applied, for example, normalising the number of user ratings for apps based on the number of downloads and/or population of the countries the apps are functioning. We will benefit from existing visualisations. Examples might include the overlaying of the type of application on the application publishing timeline to get a better view on the requirements' landscape. We also want to improve our understanding of the differences between COVID-19 apps released in EU and non-EU countries by analysing different attributes.

For the longer-term research, we see a value to investigate the following areas.

- Contextualize the apps' privacy features within the broader data infrastructure of the apps.

- Examine the partnerships and consortia behind COVID-19 related apps, between private and public and other parties in general.

- Investigate user ratings and comments for their implications on uptake.

- Explore peoples' acceptance of apps, esp. related to data handling.

- Understanding the role of Apple and Google in mediating data flows in contact tracing apps.

- Geographic analysis of tweets.

1 Introduction and scope

COVID-19 emerged as a pandemic and lead to a multi-faceted global crisis. Among others, it triggered the collection and integration of data, not only about infections and their distribution but also about human behaviour. At the same time, we witnessed the diverse and quickly emerging use of old and new digital tools. The work presented in this technical report focusses on a subset of such tools: mobile applications (apps). It is part of our work on the digital transformation of governance, including also implications on the provision, access and use of information.

From April 2020 onwards, we started collecting and analysing mobile apps provided from the two most prominent app stores: Google Play (for Android-powered devices) and the Apple App Store (for iOS-powered devices). Simultaneously, we started collecting tweets on the topic and created a dedicated collection of news items from [JRC's European Media Monitor (EMM)](#).

This document presents the technical details of our multi-channel approach to the monitoring and analysis of COVID-19-related mobile apps. The technical work described here is intended as a baseline for follow-up scientific publications on the topic. We first provide some of the technical background (Section 2) before detailing the methodology that we applied for data collection and analysis (Section 3). We present the results in Section 4 and we summarise the current findings from this exercise briefly in Section 5. We conclude with an outlook to related work and by outlining our next steps (Section 6).

2   Background and tools

With the goal to improve our understanding about the emergence and evolution of COVID-19 related apps, we decided to consider three prominent sources of information.

1. We started exploring the publication of apps in Google Play and Apple App Store. This is to understand, which apps are developed and made available to a large public.
2. We are interested to explore how people react to these developments and if some apps spark more discussions than others. Being fully aware of biases in the approach, we decided to focus related investigations on Twitter as one of the most used social media platforms of our times.
3. We investigated the mentioning of COVID-19 related apps in prominent news media to cover the media attention and thereby an important means of dissemination and opinion forming. This part of the work was built on an already existing media scraping tool (the EMM).

2.1   App store monitoring

We decided to monitor the two most popular mobile app stores, App Store (for the iOS operating system) and Google Play (for Android) and monitor them for both releases and updates of mobile apps aiming to address the COVID-19 pandemic. The app stores are analysed daily, and the data retrieved are processed once a week; this way, we maintain a database of the relevant mobile apps available together with the metadata describing them. This information is complemented with the results of manual analysis we perform on the mobile apps, in order to get some descriptives on the available mobile app landscape.

At the technical level, we use the iTunes Search API to retrieve the app descriptions from the App Store and the Node.js module "google-play-scraper" for the Google Play. Data integration and analysis are performed using the Extract Transform Load (ETL) tool FME (Feature Manipulation Engine), which also launches all the search APIs and lookup searches daily (we use the FME Workbench application of FME Desktop 2019.2.1). We also use Microsoft Translator (Version 3.0) to automatically identify non-English app descriptions and translate them into English.

2.2   Mining tweets

Evidence for Twitter's popularity is provided at Synthesio's Social Media Usage Series. On 15/03/2020 we started harvesting relevant streamed tweets using the publicly available Twitter API (and the tweepy library on top of it for better streaming support) to get the feeling of the Twitter activity about COVID-19 mobile apps. The tweets harvested contain the "COVID-19" keyword and the collected dataset is subset by filtering based on more specific keywords (such as, contact-tracing, mobile-app, etc. The full list of keywords is available in Appendix B). We are using the elastic stack for data management, querying and further data exploration and visualization (i.e. elasticsearch for data management and kibana for analysis and visualization).

2.3   Listening to the European Media Monitor

EMM monitors and aggregates about 300,000 news articles per day from news portals worldwide in up to 70 languages. We prepared, in close collaboration with the JRC's EMM team, a dedicated category based on keywords to understand the media propagation of information on COVID-19 apps. We use the EMM to better understand how the apps are being communicated to citizens in the different countries. For consistency across the different data collection channels, we reused the same keywords as those for Twitter. This allows us to gain insights on the debate on social media and media outlets in a structured manner. The data from the EMM is consequently compared with the results from Twitter.

3   Methodology

Each of the three channels is processed separately, but we occasionally benefit from interconnections. The app stores are our primary information sources, in the sense that we retrieve app descriptions from them on a regular basis (using a defined set of search terms), we retrieve relevant information automatically and then carry out a manual analysis of the most relevant apps in more detail. The scraping of Twitter applies pre-selected hashtags and terms, but it is also used to filter particularly interesting apps. The high amount of data (tweets) received allows for an exploratory approach to find patterns and clusters of messages or users. In the case of EMM, we primarily use the news that are again collected for a predefined set of search terms, on an occasional basis to find relevant news entries for a given app.

3.1   Retrieving knowledge from the Apple and Google app stores

The overall processing workflow for the information originally coming from the app stores, including further automatic processing, manual analysis, and graph creation is shown in Figure 1.
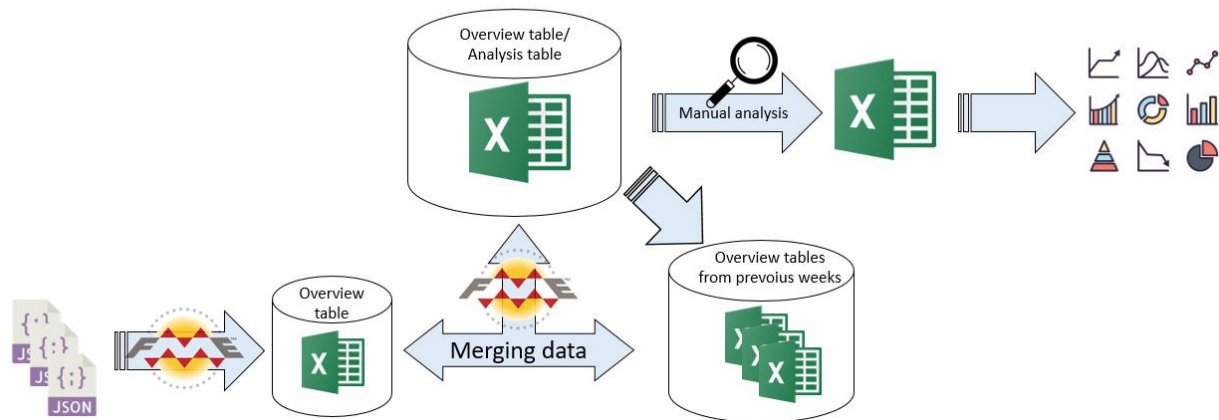
Figure 1: The overall workflow from automatic processing to manual analysis and graph creation

To retrieve the relevant information from the app stores, we look them up using keywords (terms) that were selected semi-automatically. We first got the list of COVID-19 related apps available in one single country (Italy), quickly went through the apps retrieved, and finally identified the most appropriate combination of keywords for retrieving them in each of the country stores. We ended up with the following keywords: coronavirus, corona, covid, sars-cov-2, symptoms, track, virus, social isolation, and self-diagnosis.

To retrieve the relevant information for an app, at least one of the above keywords (or a combination of the above keywords) should appear: (a) in the brief description or title of the mobile app in Google Play; (b) in the app name, app subtitle, app description, app keywords, or app reviews in the App Store. The metadata are stored in JSON format.

After the initial step of retrieving app metadata from the two app stores (a process repeated every Sunday evening), the raw data is used to create an overview table that contains the attributes of interest. Since the attribute names in the different stores may differ, although they are often semantically equivalent, we map and merge them in a unique overview table (see Section 3.1.1 for details). The overview table contains all the available versions of each app and the release dates, thus allowing us to create timelines for both app releases and app updates.

Many attribute values are retrieved directly from the app stores or are automatically derived by an ETL procedure, which also cross-checks if an app is available in both app stores. This additional step

is necessary because the look-up models used in the stores are not always efficient enough and, depending on the search algorithm, may return non-comprehensive lists of apps.

Additional information is then added to the app records manually. This includes, for example, geographic coverage, type of app provider, etc. The manual analysis is performed by a team of six researchers, based on the app descriptions retrieved from the stores. If the description is not available in English, we use the result of the automatic translation as input – anyway, the apps are not installed and thoroughly tested. We further indicate if we consider specific apps particularly interesting, for example, because they are provided the EU, they offer contact tracing functionalities, or specific user data is shared with a third party. For the apps that are considered interesting we investigate a set of additional attributes. The final results are captured in a single 'master' table for further analysis (see Section A.2 of Appendix A).

3.1.1   Automated store monitoring

Automated monitoring of the Apple App Store and the Google Play, as well as the subsequent processing, take place at the beginning of each calendar week and deliver a JSON file with the most basic information. From the app store look-up, we retrieve the attribute values and store them in the overview table (for details in the attributes, see Table A.1 in the Appendix). For all app descriptions that are not already provided in English, we automatically detect the language of the app description and translate it into English, to assist the manual analysis. This data is integrated with the data retrieved in the previous weeks, to keep track of the different versions and update dates of the apps.

3.1.2   Manual analysis of the results

We developed the framework of app functionalities of Table 1 to classify the mobile apps retrieved from the stores. Using this framework, we first classify the apps based on their category (i.e. COVID-19 specific; COVID-19 influenced; health-generic; other), we continue with the classification of the functionality offered and end up with the actual app functionalities.

App category	Functionality category	Functionality
COVID-19 specific; COVID-19 influenced; health-generic	*expert support*	monitor overall situation
		manage test
		recruitment
		telemedicine
		help in self-isolation
		training
	information provision	statistics
		prevention
		medication
		news
		access to health services

	personalised support without data sharing	self-diagnosis without data sharing
		symptoms monitoring without data sharing
		risk assessment without data sharing
	information exchange	self-diagnosis with data sharing
		symptoms monitoring with data sharing
		risk assessment with data sharing
		manage self-isolation
		communication with a doctor
	contact tracing	proximity tracking
		continuous location sharing
		occasional location sharing
	notifications	sending notifications
		sending instructions
	lockdown management	mobility for citizen in lockdown
		exit management
		mobility checking
	other-health	
other	*other*	

Table 1: Framework of app functionality characterization

During the subsequent manual analysis, we add the values of the following attributes for all the apps (more details in Appendix A, Table A.2):
- interestingApp: A yes/no value, indicating if an app is interesting for more in-depth analysis according to the focus of our study. Criteria for flagging an app as interesting are: it is EU-based, it does offer contract tracing functionalities, it does include interesting data-sharing functionalities (e.g. particular user data is shared with a third party). Although this step is partially subjective, it helps us to focus the following investigations only on a subset of the apps.
- HealthEntityInvolved: A yes/no value, indicating if a health authority has been involved in the development/distribution of the app or in the use of data collected by the app.
- providerCategory: The type of organisation that distributes the app. Allowed values: *Universities and research centres; Technology companies; Other types of companies; Non-profit organizations; National governments; Local/regional governments; Health companies; International organizations; Communities*. If it is a health authority, we use 'local/regional government' or 'national government' and fill with the value 'yes' the attribute 'healthEntityInvolved'.
- EU: A yes/no value, indicating if the app is released in an EU country.

- geographicCoverage: Countries where the app is available and functioning (according to its documentation).
- appCategory: Category of the app, according to the *Framework of app functionalities* of Table 1. Allowed values: *COVID-19 specific; COVID-19 influenced; health-generic; other*.
- AppFunctionalityCategory: Category of the app functionality, according to the *Framework of app functionalities* of Table 1. Allowed values: *expert support; information provision; personalised support without data sharing; information exchange; contact tracing; notifications; lockdown management; other-health; other*.

The following information is added manually for the apps of interest:
- AppFunctionality: App functionalities, according to the *Framework of app functionalities* of Table 1. Allowed values: *monitor overall situation; manage test; recruitment; telemedicine; help in self-isolation; training; statistics; prevention; medication; news; access to health services; self-diagnosis without data sharing; symptoms monitoring without data sharing; risk assessment without data sharing; self-diagnosis with data sharing; symptoms monitoring with data sharing; risk assessment with data sharing; manage self-isolation; communication with a doctor; proximity tracking; continuous location sharing; occasional location sharing; sending notifications; sending instructions; mobility for citizen in lockdown; exit management; mobility checking*.
- typesOfPersonalData: Type of personal data collected by the app. Allowed values: *Proximity; Location as province/region; Location as GPS/cell tower data; Health status; Positive status; Other*.
- clearPrivacyPolicy: A yes/no value, indicating if the app clearly communicates what information it collects and how it processes it.

3.2 Gathering data from Twitter

We started harvesting tweets with keywords relevant to COVID-19 and mobile apps (see Appendix B for the full list of keywords) on 15 March 2020 and kept collecting them ever since. Notably, this is done using the publicly available API, i.e. we do not retrieve all tweets with the targeted keywords, but only a subset.

3.3 Setting up a new category for the European Media Monitor

A dedicated category was prepared by reusing the same keywords as the ones defined for Twitter (available in Appendix B). This ensures consistency and comparability between the spatio-temporal distribution of the occurrences of mentions of the predefined terms.

4 Results

In terms of data, as already mentioned above, we are using three data sources: data from the mobile app stores, Twitter data and EMM news items. We outline here the datasets (essentially data snapshots) we have used to get the first results.

The data stored about apps includes attribute values retrieved from the stores and attribute values resulting from a manual analysis (see Section 3.1 for the methodology and Appendix A for the full list of attributes). The dataset we used for the graphs that give us the first descriptives on the COVID-19 apps is a data snapshot with the following features:

- 837 records, each describing one mobile app and including both automatically retrieved attribute values and manually evaluated ones.

- The time interval that the stores have been monitored for this data snapshot is 20/04/2020-02/08/2020.

The tweets about COVID-19 (more than 233 million tweets on 12/11/2020), collected since March 15th, 2020. More details are available in Section 4.3, where specific parts of the collected data set are highlighted.

For a period of approximately seven months (between 07/04/2020 and 12/11/2020) we collected through the EMM a total of 4442 articles. Figure 2 below provides an overview of the weekly distribution of the data during this time interval.

Week	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
Series1	329	510	512	515	357	213	248	172	209	52	202	94	57	86	39	64	29	41	98	58	32	42	41	50	106	42	53	46	62	22	33	28
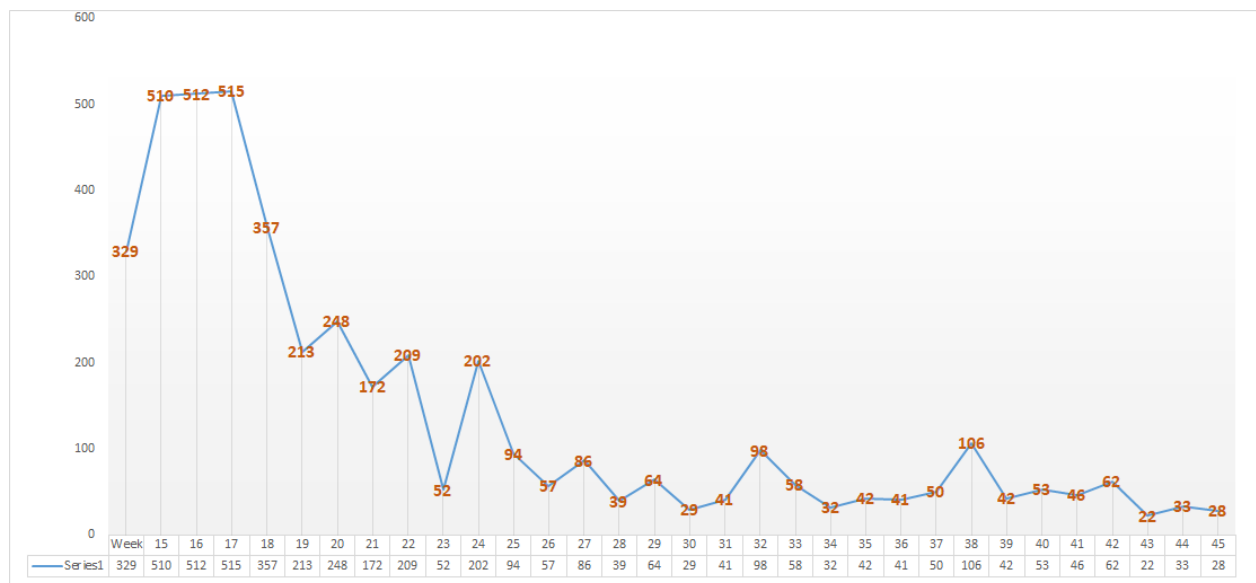
Figure 2: Overview of the weekly distribution of the EMM articles collected in the time interval 07/04/2020 and 12/11/2020

The dataset that resulted from app store monitoring and the subsequent manual analysis, should be shared on the JRC Data Catalogue, once the analysis is completed and we publish our findings. Initial results from tweet analysis, together with relevant visualisations are shared on the GitHub organization of the Innovative Public Service Observatory. The dedicated EMM category described in Section 3.3 is available online. The landing page provides an overview of the most recent news. The data is also available through an RSS feed for further web integration and/or processing. In addition, a geolocation representation of the data is available through (I) a web map, and (ii) for download as a KML file.

4.1 Descriptives emerging from app stores

The above-mentioned approach allowed us to create a series of graphics from the data gathered. The graphics with a brief explanation are presented below.

First, we looked for some descriptive information about the activities in the app stores, such as how many apps have been published in each of the stores, the timelines of new app publication and app updates in each of the stores, as well as, the geospatial distribution of the apps. Among the 837 apps in our dataset, 359 apps were found on App Store only, 229 apps on Google Play only, and 249 apps on both stores, as is shown in Figure 3.
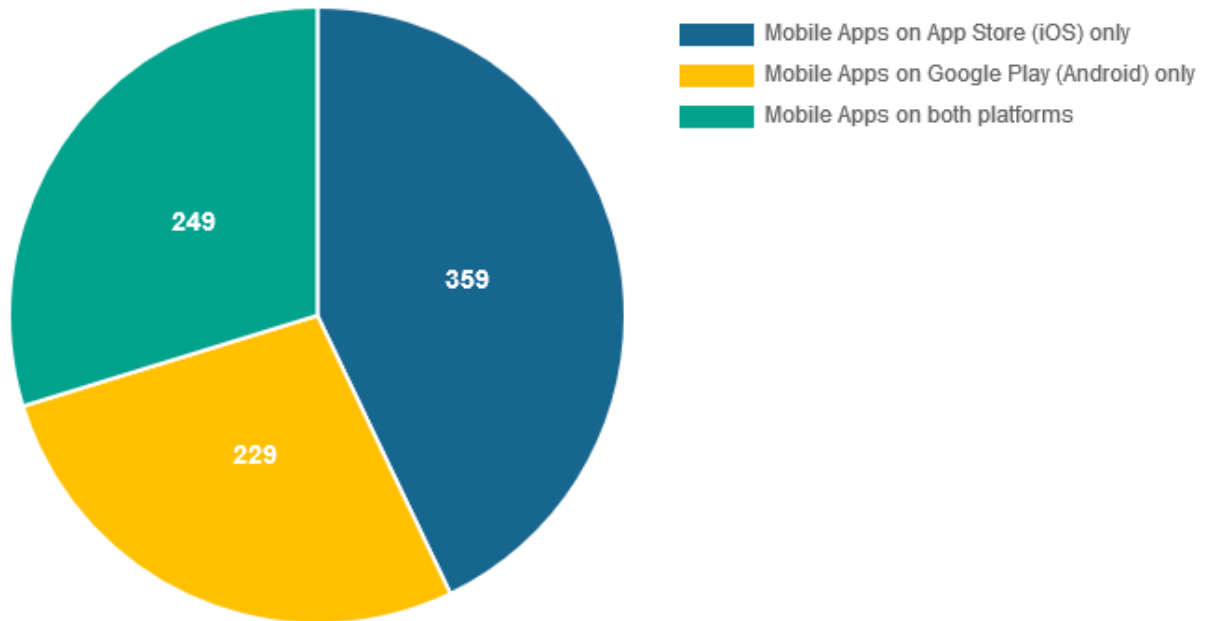

Figure 3: Distribution of the apps in the app stores

The timelines of new app releases and app updates in both stores are shown in Figure 4 and Figure 5, respectively. These timelines show that new app releases indeed started slowly in January, with the increase of releases in both stores starting from February, reaching the maximum number of new releases at the end of March 2020. Figure 4 indicates that the number of released apps in Google Play prevailed until early April 2020, while in the App Store significant numbers of new app releases continued until the end of June. It is also evident from both Figure 4 and Figure 5 that the number of new app releases and updates is lower in the weekends. This is clear in the visualisation for 30/03/2020 since it highlights the period 28/3(Saturday)–30/3(Monday). Note that both the app release date and the last app update are among the app attribute values harvested from the stores (see Appendix A, Section A.2 for details). Therefore, we have identified app releases and updates before we started monitoring the stores.
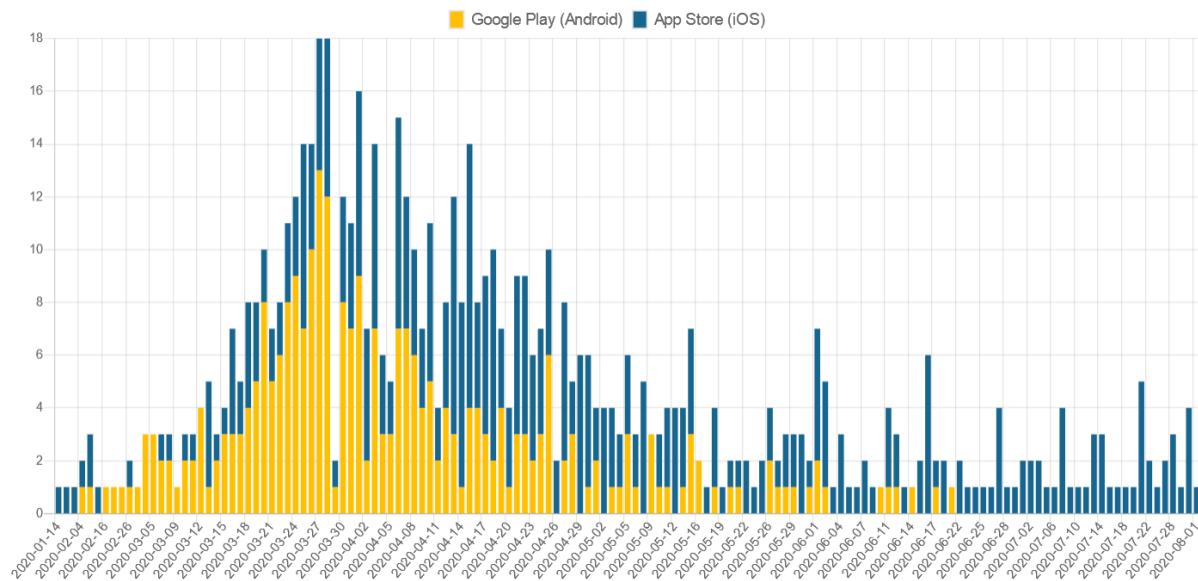
Figure 4: App release timeline. The X axis shows the app release dates and the Y axis the number of apps released.

Furthermore, Figure 5 shows that the apps were constantly updated on both stores; a combined look at both the timelines of new app releases and app updates clearly indicates that app updates were necessary after new app release and usage, starting from early April 2020.
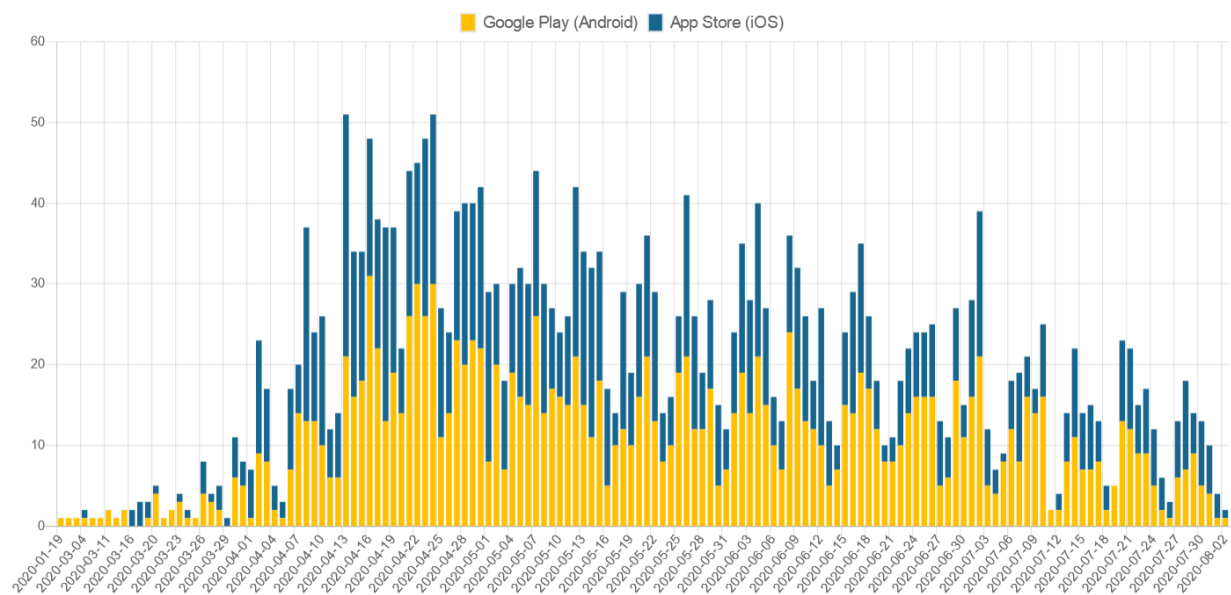
Figure 5: App update timeline. The X axis shows the app update dates and the Y axis the number of apps updated.

Considering the geographic coverage of the apps (i.e., for which country/ies each app has been released), we identified 15 apps with world-wide coverage, for example, those developed by international organisations such as the WHO and the UN. Figure 6 shows the geospatial distribution of the additional, country-specific apps, developed for a total of 98 different countries. The country with most apps is the US (153), followed by India (86), Brazil (55), Mexico (35) and Spain (30). The distribution of such values is left skewed, with a median value of 3 compared to an average value of 8.7. Indeed, more than 50% of the 98 countries have less than 4 apps, with 25 countries having only 2 apps and 17 countries having only 1 app.
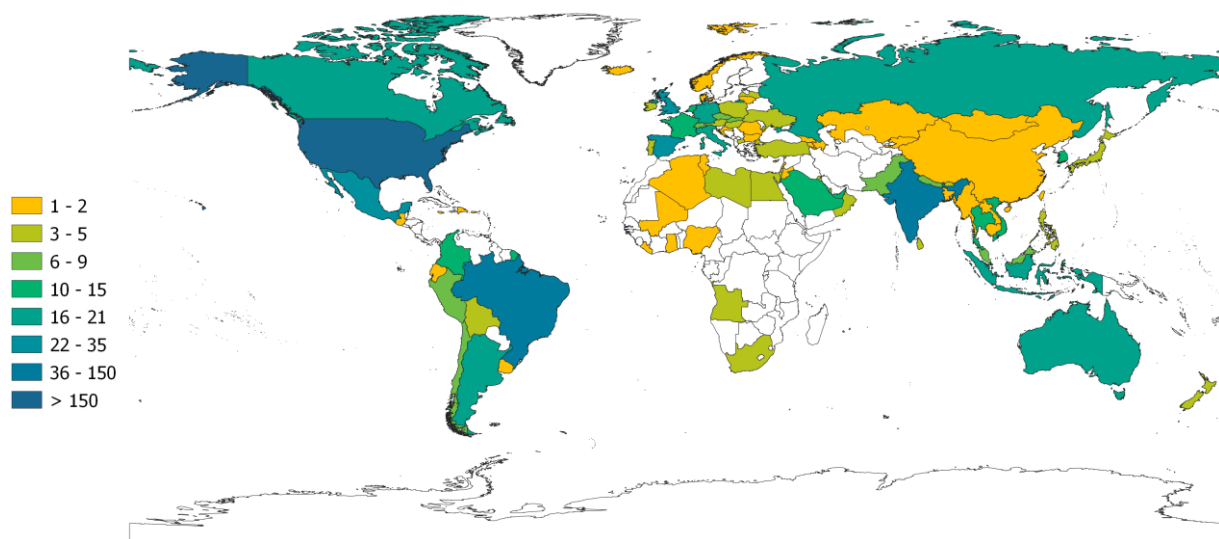
Figure 6: Geospatial distribution of the country-specific apps released. There are also 15 apps with world coverage.

We complement these statistics with an indication of the apps that attracted much interest. The indicator we use for this is the number of user ratings each app received, and the results are shown in Figure 7 and Figure 8, with the top 8 most rated COVID-19 related apps in Google Play and App Store, respectively (notice that "most rated" does not mean "best rated" – rating often comes out because of bad user experience). According to Figure 7, the most rated app in Google Play is "Aarogya Setu", followed by "CAIXA|Auxílio Emergencial" and Mobile JKN. Figure 8 shows that "Aarogya Setu" is the most rated app also in App Store, now followed by "COVID Symptom Study" and "Doximity". Notably, "Aarogya Setu", "COVID Symptom Study" and "Corona-Warn-App" are among the 8 most rated apps in both stores.
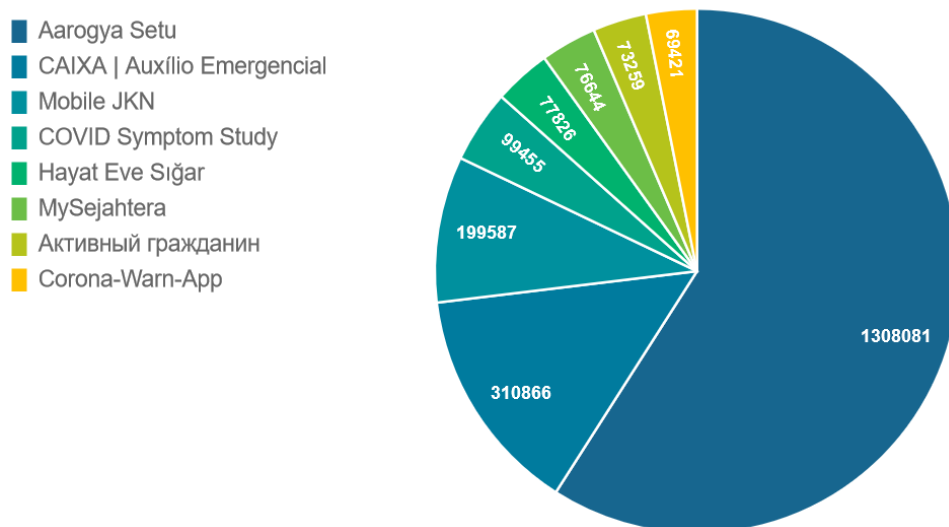
Figure 7: Top 8 most rated COVID-19 related apps in Google Play
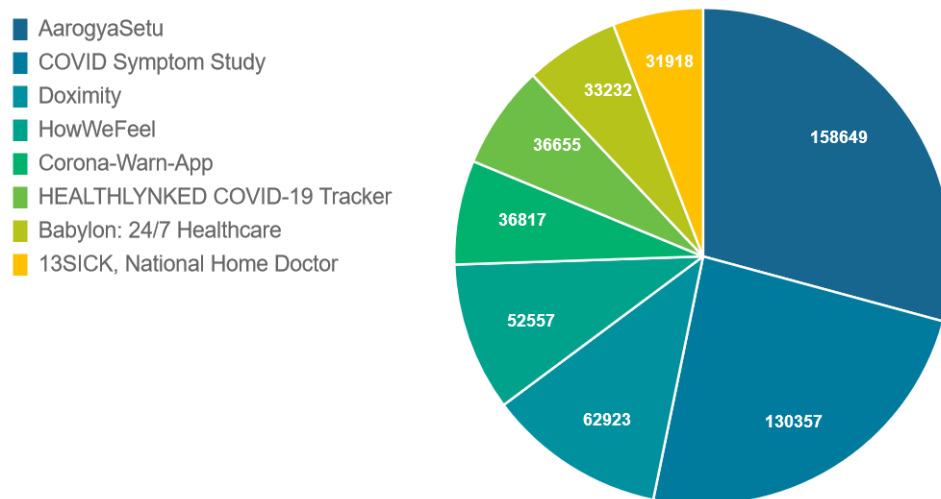
Figure 8: Top 8 most rated COVID-19 related apps in App Store

More qualitative information was revealed by the manual analysis, including the identification of apps that we considered interesting (because of their functionalities) and contact tracing apps, as well as their geospatial distribution (at the EU/non-EU scale), their category and the category of the app providers. As a result, 259 apps (i.e. 31% of the total number of apps) were identified as interesting, i.e. worth to examine in more detail. Among the 259 interesting apps, 138 apps were also identified as contact tracing apps, as shown in Figure 9.
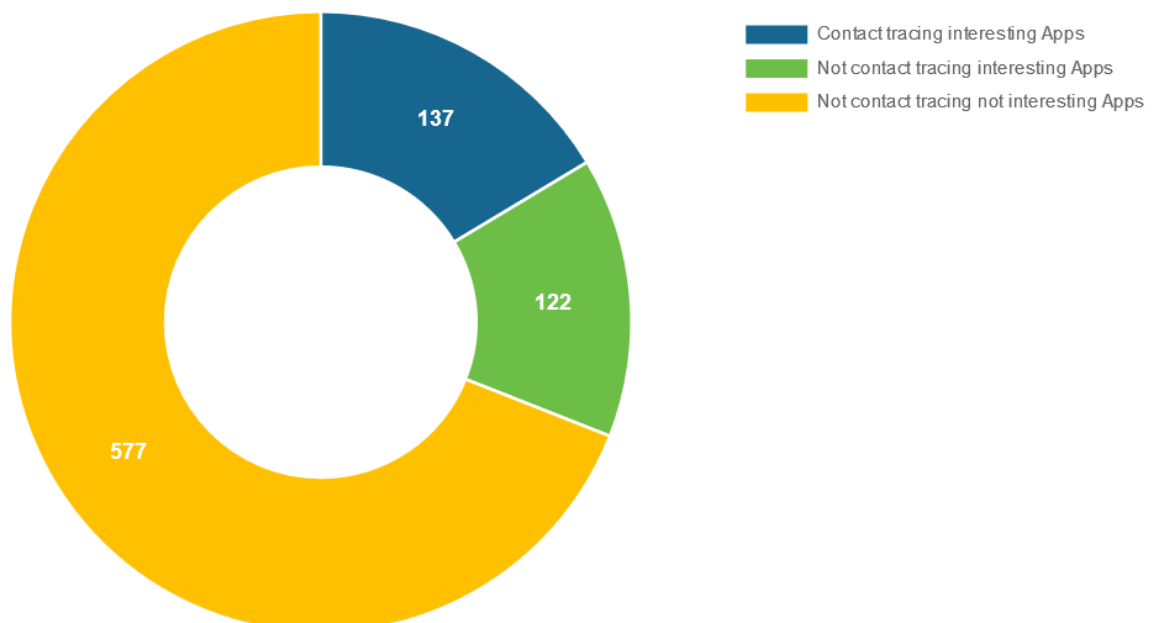
Figure 9: Share of interesting apps and contact tracing apps

183 apps were released in at least one EU country, while 654 apps were not released in any EU country. This distribution, together with that of interesting apps, is shown in Figure 10.
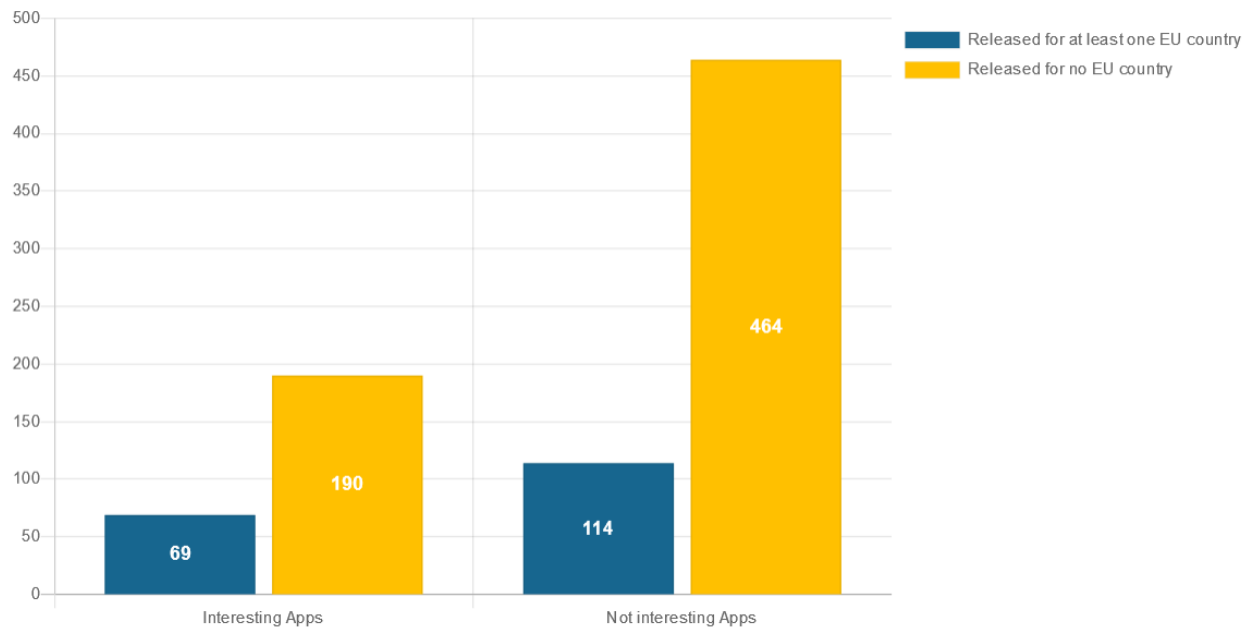
Figure 10: Distribution of interesting/non interesting apps inside/outside the EU

We also identified the category each app belongs to and created the graph of Figure 11, highlighting that the dominant category is the COVID-19 specific apps on both stores, followed by the generic health apps.
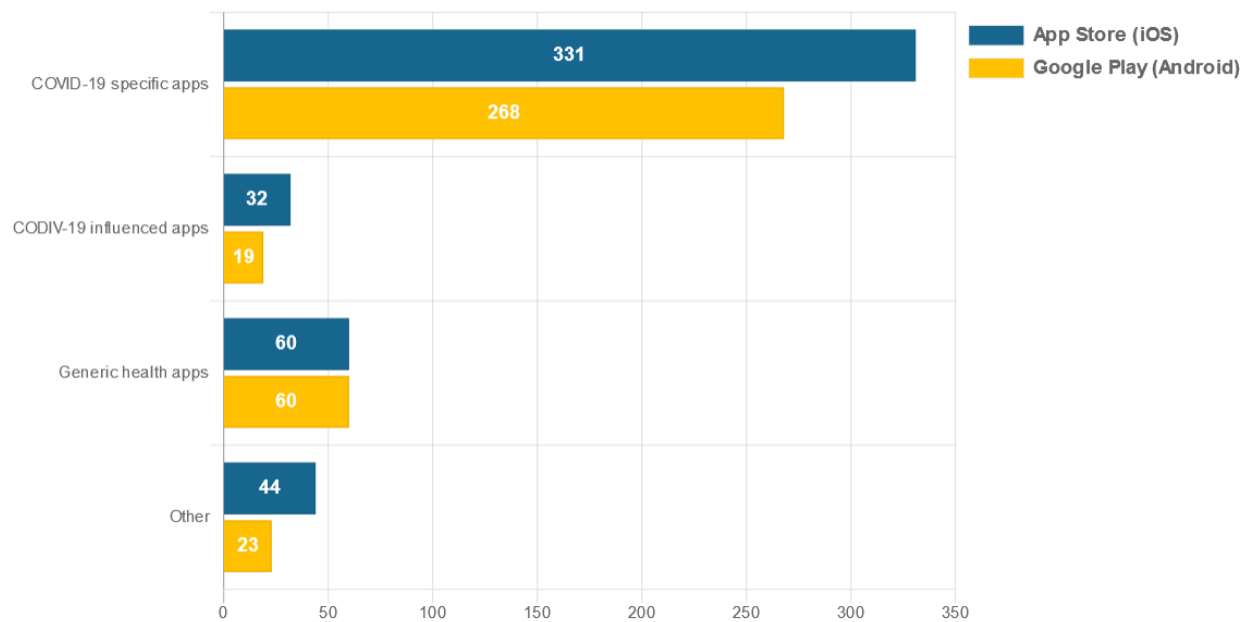
Figure 11: Distribution of the apps in the different app categories

Last but not least, we identified the app provider categories and depicted their distribution in Figure 12. According to Figure 12, most of the apps were provided by the public sector (local/regional or national), followed by the ones released by health companies and other types of companies.

Figure 12: Distribution of the app provider categories

4.2 Descriptives emerging from Twitter

Given recent intense public debates about the use of mobile apps and data, we used the collected dataset of tweets to analyse this discourse in more detail. A set of visualisation tools (gephi and sigma.js) was put in place that allows us to get visual clues.

The first outcome was the hashtag network of Figure 13, created for a subset of the dataset that includes tweets harvested between 15/03/2020 and 19/04/2020 (around 5.3 million tweets about COVID-19, all in English and with hashtags). This hashtag network is also available as a high-resolution image and an interactive hashtag network.

Figure 13: Hashtag network for tweets with the "COVID-19" keyword, harvested between 15/03/2020 and 19/04/2020

The next objective was to get a feeling about the public opinion. For this reason, we performed sentimental analysis on that same dataset. The word clouds of the top-50 negative and positive hashtags are shown, respectively, in Figure 14 and Figure 15. The top 50 positive and negative hashtags have been extracted from the hashtag network considering the positivity and negativity of the related tweets and the relevance (node degree) of the hashtag inside the network. The font size of each hashtag in the word cloud represents its positivity/negativity level.

Figure 14: Top-50 negative hashtags for tweets with the "COVID-19" keyword, harvested between 15/03/2020 and 19/04/2020

Figure 15: Top-50 positive hashtags for tweets with the "COVID-19" keyword, harvested between 15/03/2020 and 19/04/2020

The full sentiment analysis results are again available both as a high-resolution image and an interactive hashtag network. From here, we took a closer look at apps and privacy in the COVID-19 context. The first step was to filter our dataset, using the keywords "mobile app", "tracking" and "privacy", resulting to a subset containing 175000 tweets. Then, we created the hashtag network of Figure 16 for the new dataset (also available as a high-resolution image and an interactive hashtag network). In addition, we created a hashtag network visualisation with the "COVID-19" community pruned (high-resolution image and interactive hashtag network available).

Figure 16: Hashtag network for tweets with the "COVID-19" keyword, harvested between 15/03/2020 and 19/04/2020, filtered using the keywords "mobile app", "tracking" and "privacy"

In addition, we created hashtag networks for COVID-19 and each of the keywords "tracking app" (high-resolution image and interactive hashtag network), "privacy" (high-resolution image and interactive hashtag network) and "smartphone" (high-resolution image and interactive hashtag network), among which the most interesting (in terms of network structure) seems to be that of COVID-19 and privacy that is also shown in Figure 17.
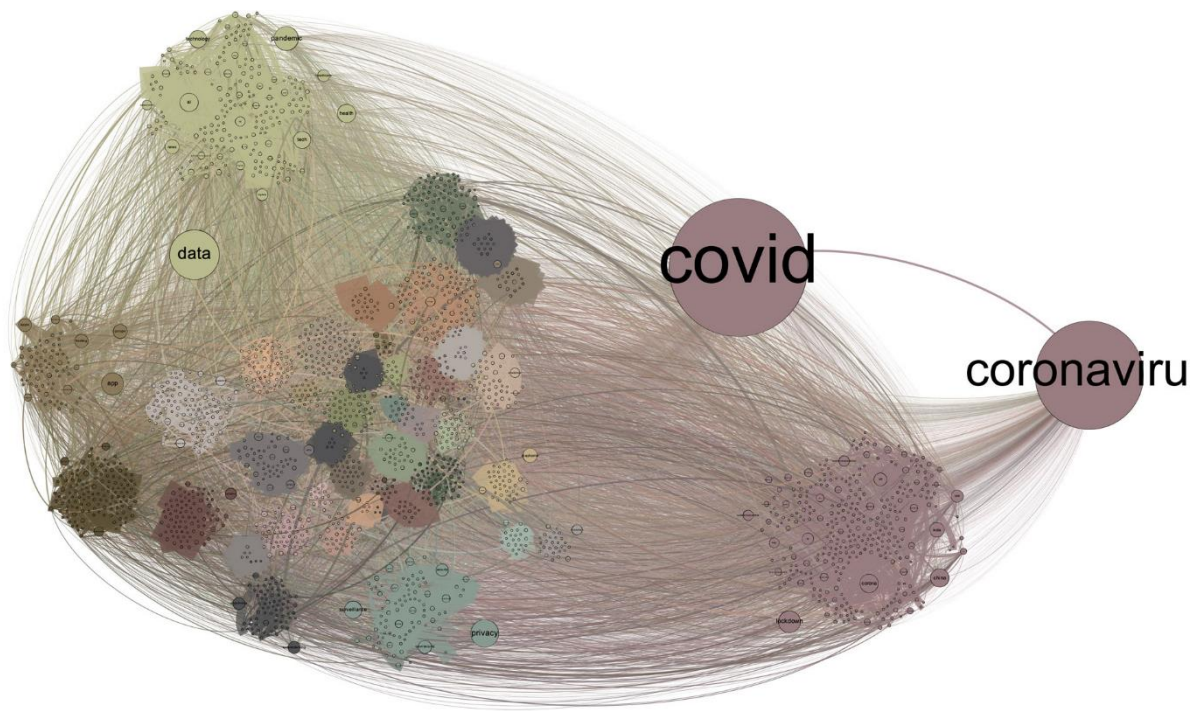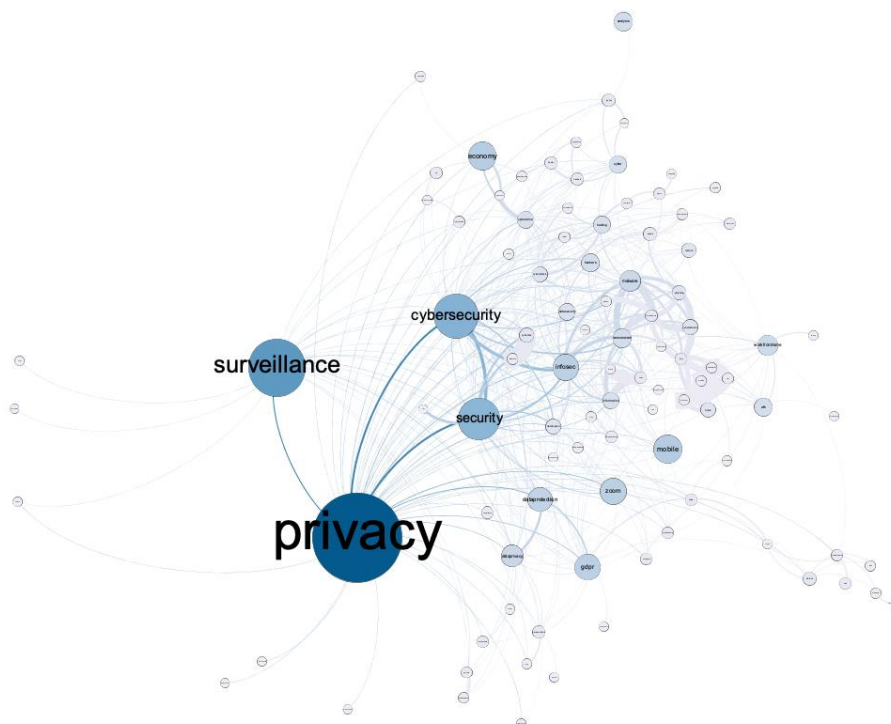

Figure 17: Hashtag network for tweets with the "COVID-19" keyword, harvested between 15/03/2020 and 19/04/2020, filtered using the keyword "privacy"

Since the Pan-European Hackathon: EU Vs Virus Challenge was organized on 24/04/2020, we collected, in the period 21-27/04/2020, 6690 tweets (8139 raw tweets) for the hackathon and used the 1336 ones with valid hashtags to create the hashtag network of Figure 18.
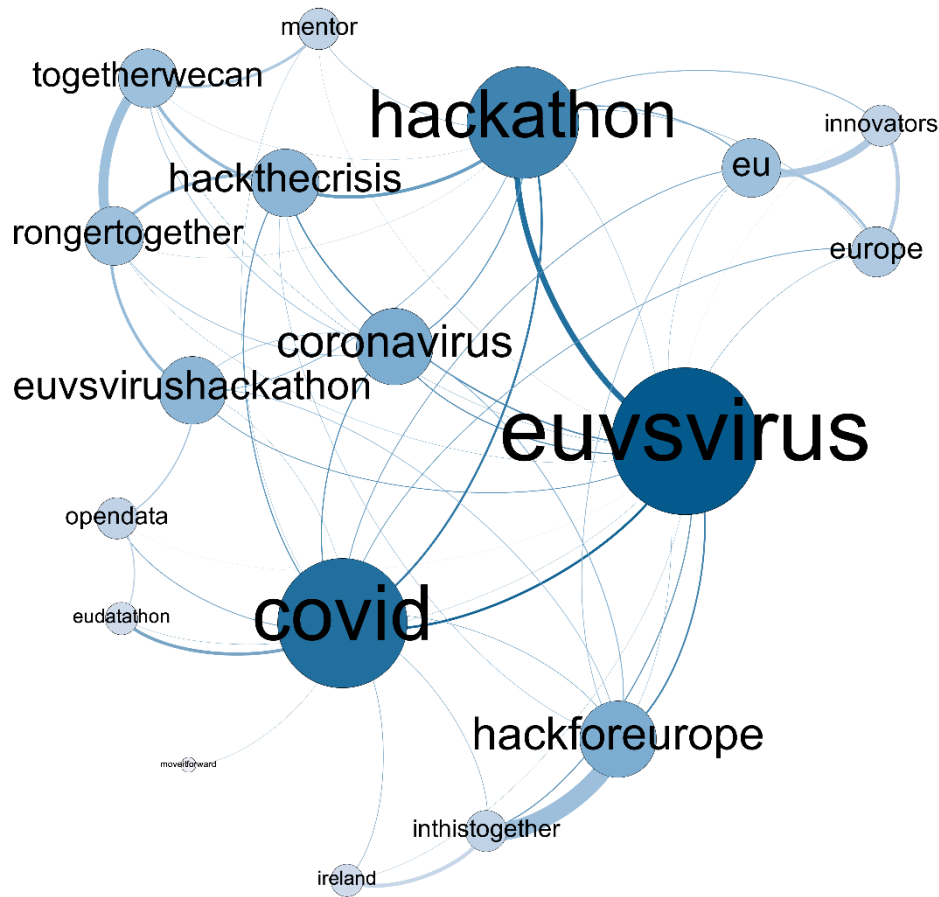
Figure 18: Hashtag network for tweets about the EU vs. virus hackathon, harvested between 21/04/2020 and 27/04/2020

By that time, the terminology changed slightly and the "tracking app" term was primarily replaced by "contact tracing app"; this reflected the focus of many governments in this direction as well as the availability of such apps. In order to get a better understanding, we filtered with keywords about contact tracing apps the streamed tweets about COVID-19 (more than 233 million tweets on 12/11/2020 collected since 15/03/2020) and created the hashtag network of Figure 19 (high-resolution image and interactive hashtag network available).
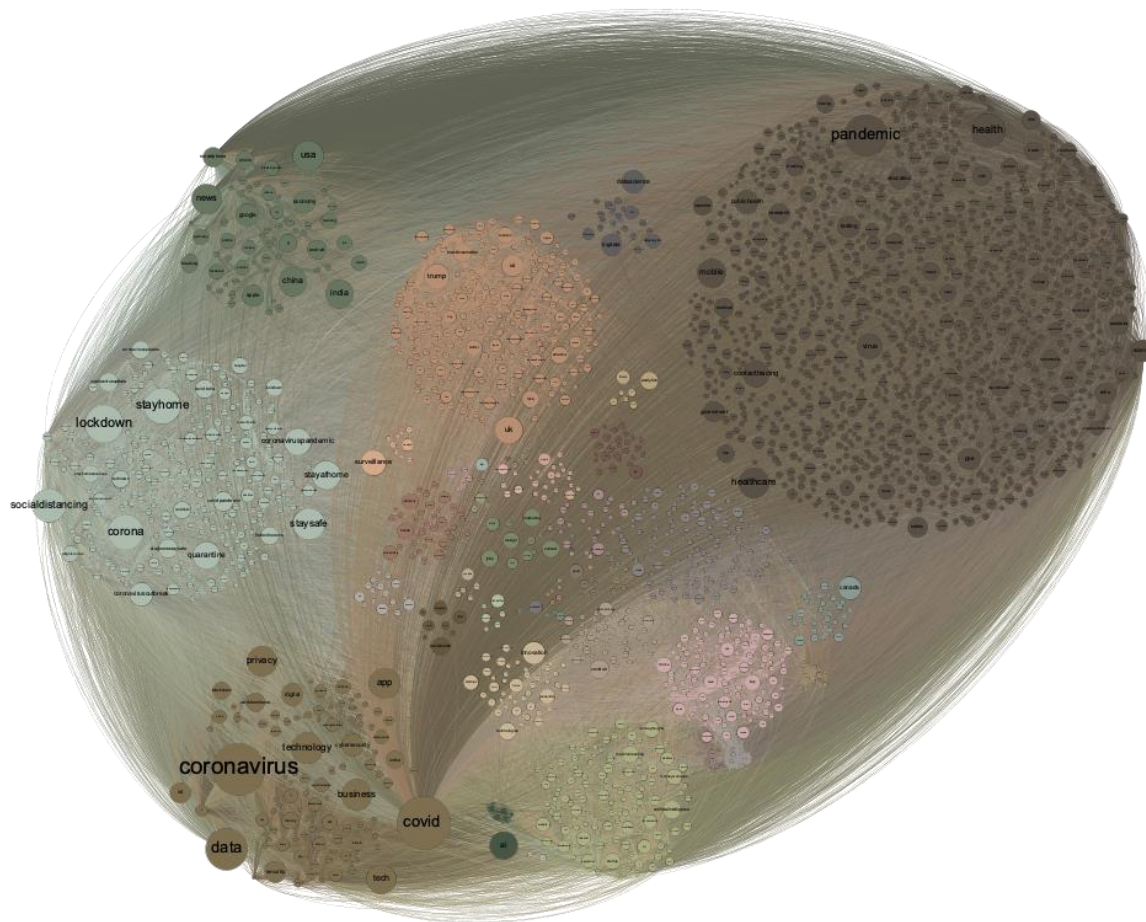
Figure 19: Hashtag network for tweets about COVID-19 and contact tracing mobile apps, harvested between 21/04/2020 and 12/11/2020

As a next step we performed sentiment analysis on that same dataset, resulting in the "classical" sentiment analysis network of Figure 20 (high-resolution image and interactive hashtag network) and the network highlighting positive/negative hashtags of Figure 21 (high-resolution image and interactive hashtag network). Most of the communities detected inside the network have sentiment polarity; especially within the small negative communities in red we have a subset of extremely negative tweets.

Figure 20: Sentiment analysis for tweets about COVID-19 and contact tracing mobile apps, harvested between 21/04/2020 and 12/11/2020

Figure 21: Sentiment analysis highlighting positive/negative hashtags for tweets about COVID-19 and contact tracing mobile apps, harvested between 21/04/2020 and 12/11/2020

The sentiment analysis also resulted in the tag clouds of Figure 22, with the top 50 negative (on the left) and top 50 positive (on the right) hashtags.

Top 50 negative hashtags   Top 50 positive hashtags

Figure 22: Top 50 negative (left) and positive (right) hashtags, resulting from sentiment analysis for tweets about COVID-19 and contact tracing mobile apps, harvested between 21/04/2020 and 12/11/2020

An indication of public interest in the Twitter context is that of popular hashtags and keywords. The tag clouds of Figure 23 show the top-50 most popular hashtags (on the left) and the top-50 most popular keywords (on the right), which resulted from the analysis of tweets about COVID-19 and contact tracing mobile apps, harvested between 21/04/2020 and 12/11/2020.

Top 50 popular hashtags   Top 50 popular keywords

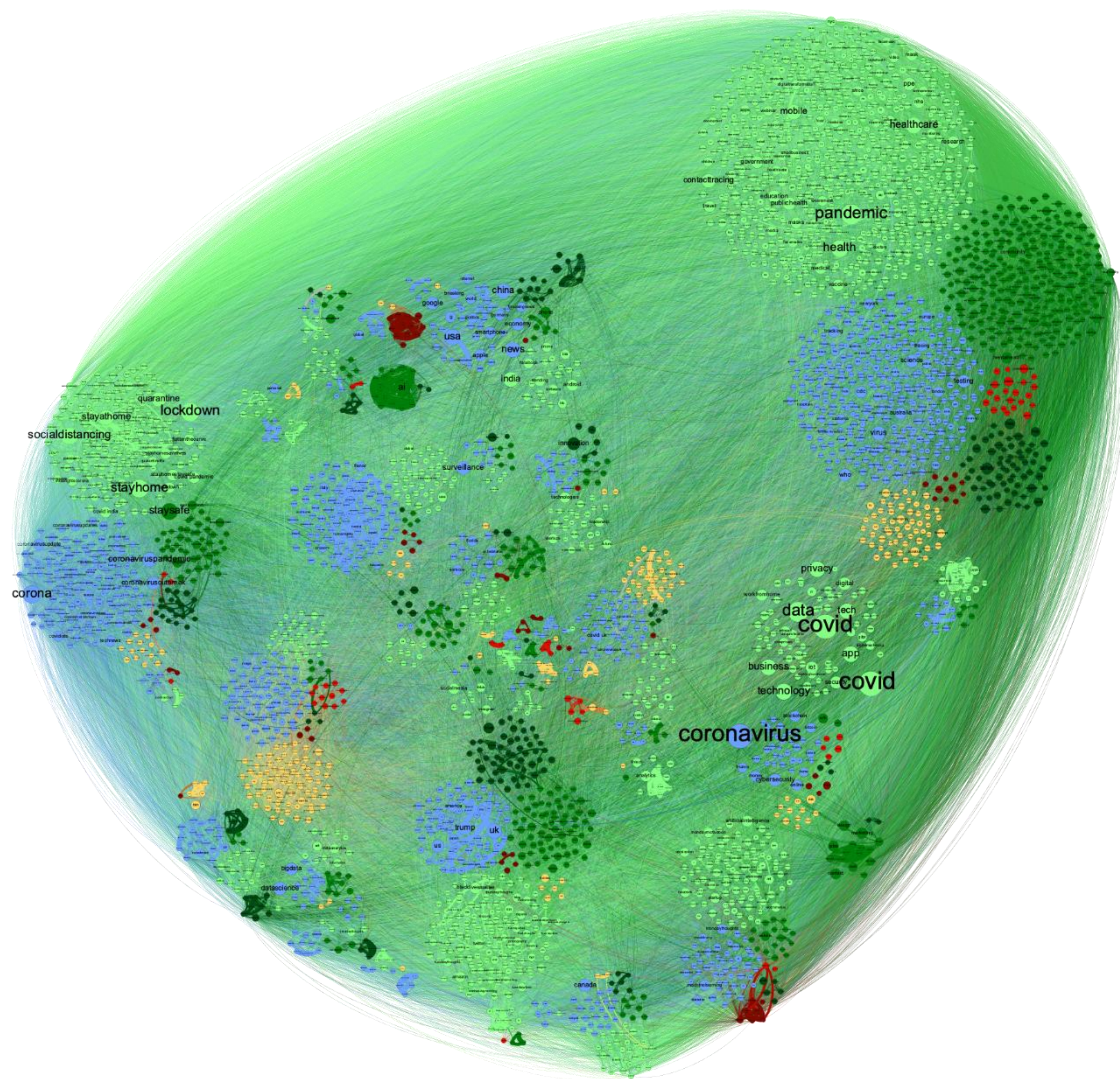Figure 23: Top 50 popular hashtags (left) and keywords (right), resulting from the analysis of tweets about COVID-19 and contact tracing mobile apps, harvested between 21/04/2020 and 12/11/2020

We then focused on European contact tracing apps and started harvesting streamed tweets about them on 09/07/2020. As of today (12/11/2020) we have collected 309399 tweets for the apps Immuni (IT), Radar Covid (ES), Stopcovid (FR), Covid Tracker Ireland (IE), Corona Warn App (DE), NHS Covid 19 App (UK), SwissCovid (CH), Erouska (CZ), Protego (PL), Smittestop (DK), Stopp Corona (AT), and Smittestopp (NO). The first outcome is the interactive hashtag network shown in Figure 24.

Figure 24: Hashtag network for tweets about European contact tracing mobile apps, harvested between 09/07/2020 and 12/11/2020

Focussing on the Twitter activity about individual apps resulted in Table 2, and a distribution of tweets as illustrated in Figure 25.

Mobile application name	Number of tweets
Immuni (IT)	87670
Radar Covid (ES)	58057
Stopcovid (FR)	48716
Covid Tracker Ireland (IE)	43100
Corona Warn App (DE)	38997
NHS Covid 19 App (UK)	24159
Swisscovid (CH)	2324
Erouska (CZ)	2124
Protego (PL)	1584
Smittestop (DK)	1075
Stopp Corona (AT)	875
Smittestopp (NO)	718

Table 2: Number of tweets, harvested between 09/07/2020 and 12/11/2020, for the contact tracing mobile apps Immuni (IT), Radar Covid (ES), Stopcovid (FR), Covid Tracker Ireland (IE), Corona Warn App (DE), NHS Covid 19 App (UK), SwissCovid (CH), Erouska (CZ), Protego (PL), Smittestop (DK), Stopp Corona (AT), and Smittestopp (NO).
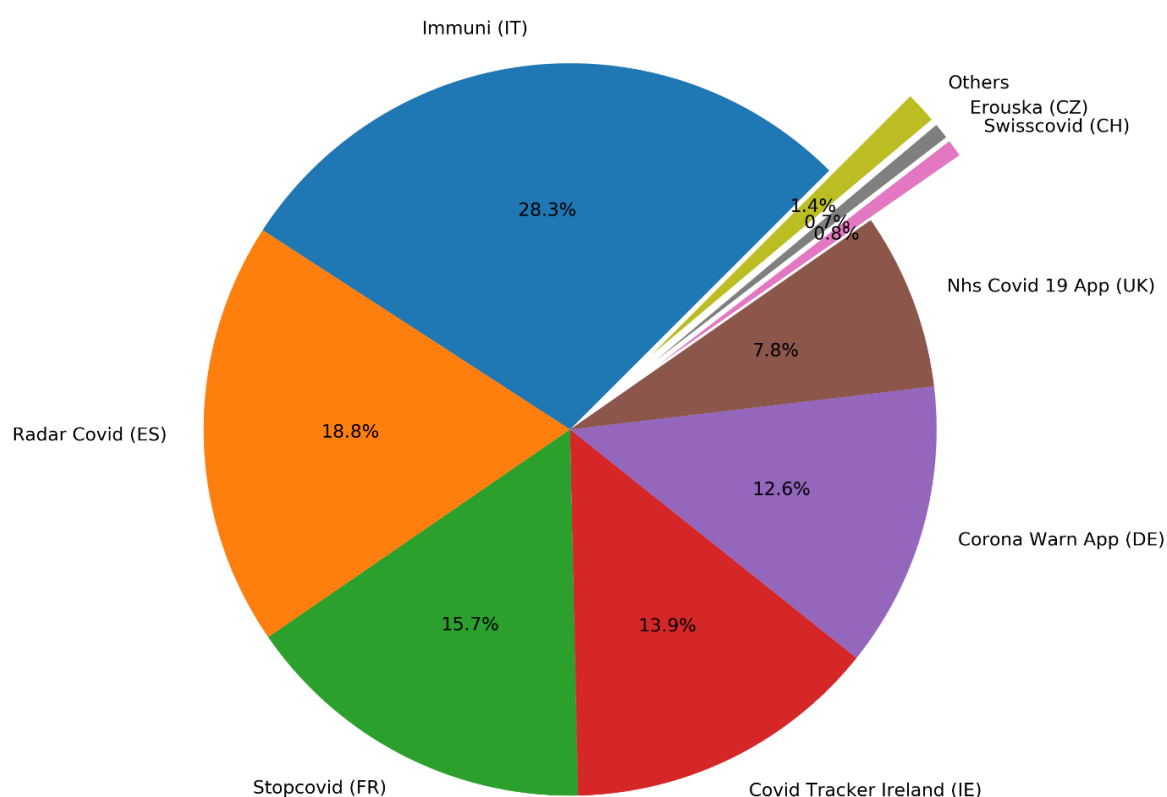

Figure 25: Pie chart showing the distribution of tweets, harvested between 09/07/2020 and 12/11/2020, for the contact tracing mobile apps Immuni (IT), Radar Covid (ES), Stopcovid (FR), Covid Tracker Ireland (IE), Corona Warn App (DE), NHS Covid 19 App (UK), SwissCovid (CH), Erouska (CZ), Protego (PL), Smittestop (DK), Stopp Corona (AT), and Smittestopp (NO)

Last but not least, we examined for the most popular apps the temporal evolution of user activity on Twitter, the temporal evolution of relevant news in EMM and the distribution of tweets in terms of languages used. As expected, the official language of each country dominates in the tweets about the mobile app released in that country. An interesting case is SwissCovid (CH), with a significant percentage of tweets in three languages, since there are three official languages (Italian, German and French) in the country.

In detail, we have:

- For Immuni (IT), 90.69% of the tweets in Italian, 6.44% in English, 0.63% in French, 0.53% in Spanish and 2.24% in other languages.

- For Radar Covid (ES), 89.66% of the tweets in Spanish, 4.33% in English, 4.02% in Catalan, 0.95% in Portoguese and 1.98% in other languages.

- For Stopcovid (FR), 70.83% of the tweets in French, 17.81% in English, 2.48% in Spanish, 2.08% in Polish and 8.89% in other languages.

- For Covid Tracker Ireland (IE), 98.04% of the tweets in English, 0.2% in Catalan, 0.17% in French, 0.15% in Portoguese and 1.58% in other languages.

- For Corona Warn App (DE), 85.86% of the tweets in German, 9.45% in English, 0.93% in Dutch, 0.65% in Spanish and 3.76% in other languages.

- For NHS Covid 19 App (UK), 98.9% of the tweets in English, 0.18% in Spanish, 0.63% in Welsh, 0.14% in Italian and 0.76% in other languages.

- For SwissCovid (CH), 49.89% of the tweets in German, 25.78% in English, 18.33% in French, 4.08% in Italian and 6.0% in other languages.

- For Erouska (CZ), 95.08% of the tweets in Czech, 2.68% in English, 0.79% in Polish, 0.25% in Basque and 1.44% in other languages.

The graphs showing the temporal evolution of user activity on Twitter and of relevant news in EMM for Immuni (IT) are shown in Figure 26, for Radar Covid (ES) in Figure 27, for Stopcovid (FR) in Figure 28, for Covid Tracker Ireland (IE) in Figure 29, for Corona Warn App (DE) in Figure 30, for NHS Covid 19 App (UK) in Figure 31, for SwissCovid (CH) in Figure 32 and for Erouska (CZ) in Figure 33. Notably no news items were available for Radar Covid (ES), SwissCovid (CH) and Erouska (CZ) as of 12/11/2020.
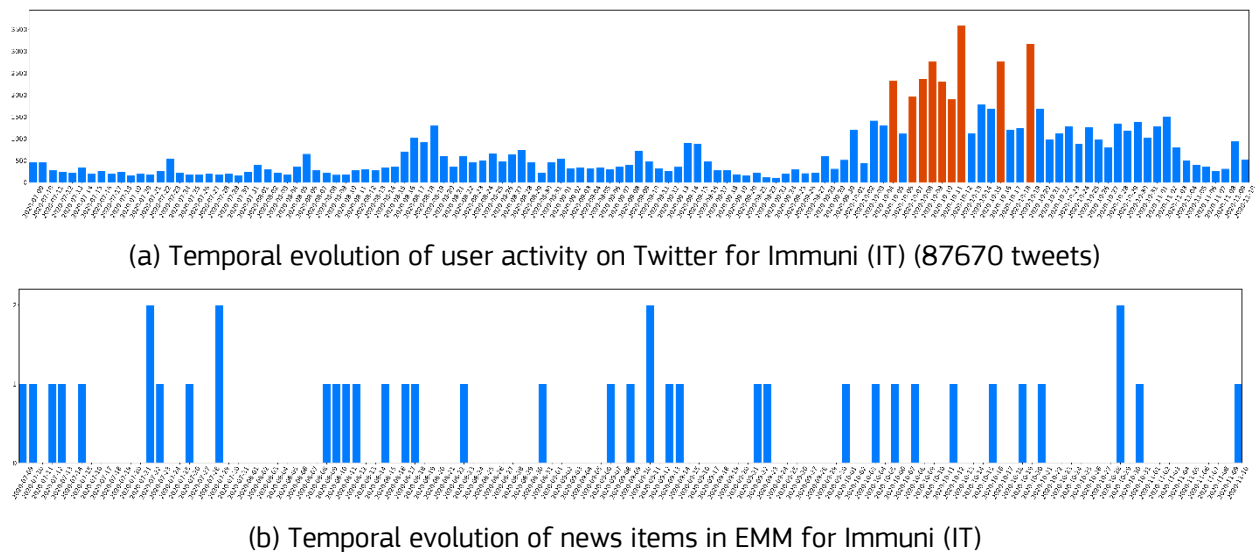

(a) Temporal evolution of user activity on Twitter for Immuni (IT) (87670 tweets)

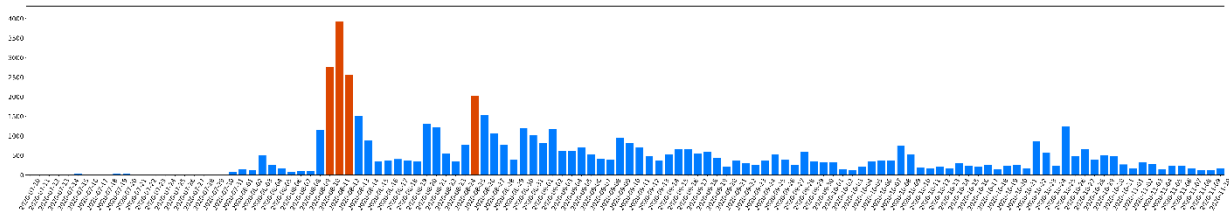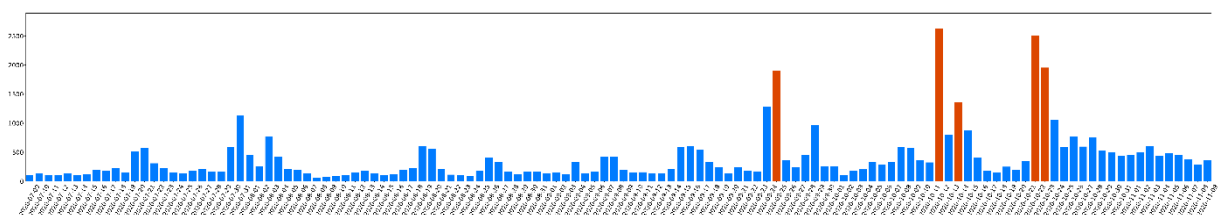(b) Temporal evolution of news items in EMM for Immuni (IT)

Figure 26: Further processing of the tweets about Immuni (IT), harvested between 09/07/2020 and 12/11/2020
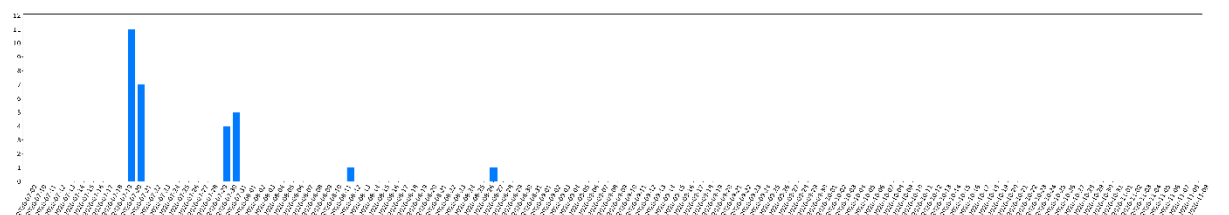
(a) Temporal evolution of user activity on Twitter for Radar Covid (ES) (58057 tweets)

Figure 27: Further processing of the tweets about Radar Covid (ES), harvested between 09/07/2020 and 12/11/2020
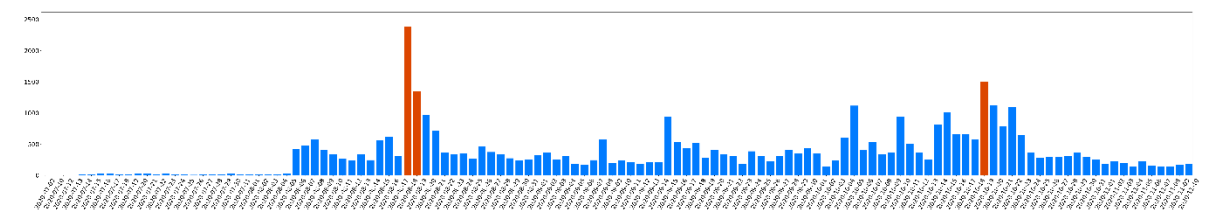

(a) Temporal evolution of user activity on Twitter for Stopcovid (FR) (48716 tweets)
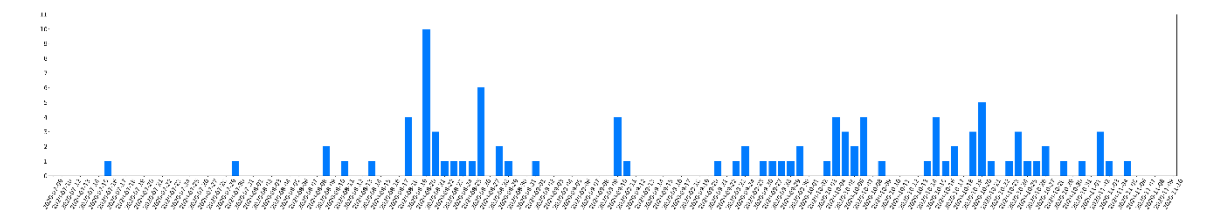

(b) Temporal evolution of news items in EMM for Stopcovid (FR)

Figure 28: Further processing of the tweets about Stopcovid (FR), harvested between 09/07/2020 and 12/11/2020
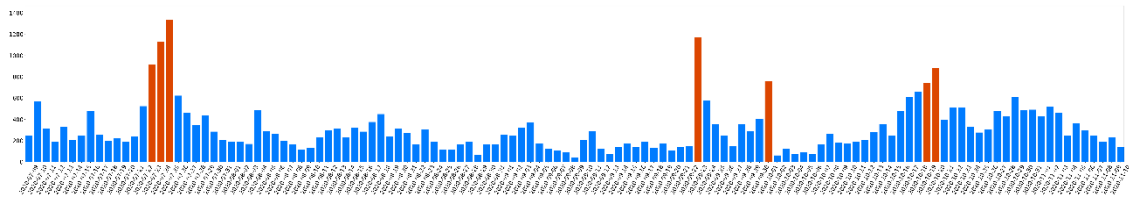

(a) Temporal evolution of user activity on Twitter for Covid Tracker Ireland (IE) (43100 tweets)
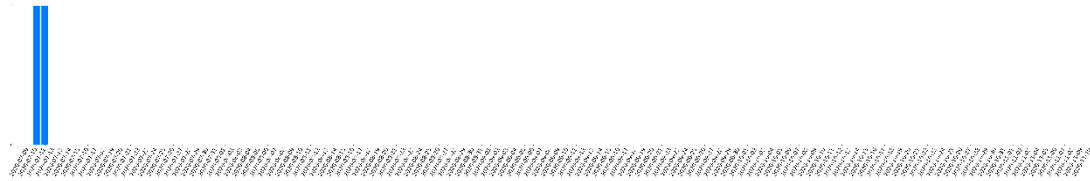

(b) Temporal evolution of news items in EMM for Covid Tracker Ireland (IE)

Figure 29: Further processing of the tweets about Covid Tracker Ireland (IE), harvested between 09/07/2020 and 12/11/2020
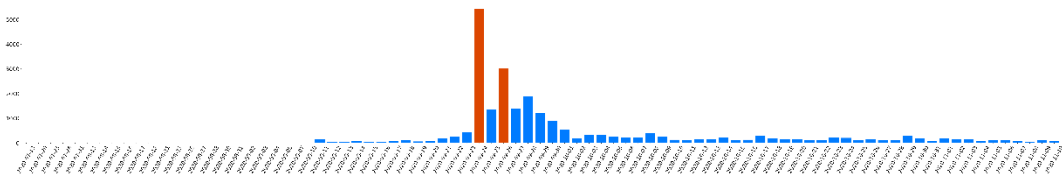
(a) Temporal evolution of user activity on Twitter for Corona Warn App (DE) (38997 tweets)
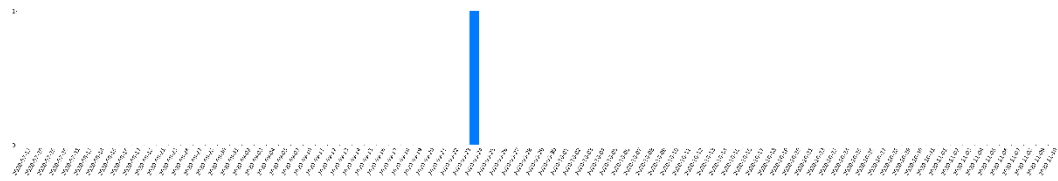

(b) Temporal evolution of news items in EMM for Corona Warn App (DE)

Figure 30: Further processing of the tweets about Corona Warn App (DE), harvested between 09/07/2020 and 12/11/2020

(a) Temporal evolution of user activity on Twitter for NHS Covid 19 App (UK) (24159 tweets)

(b) Temporal evolution of news items in EMM for NHS Covid 19 App (UK)

Figure 31: Further processing of the tweets about NHS Covid 19 App (UK), harvested between 09/07/2020 and 12/11/2020
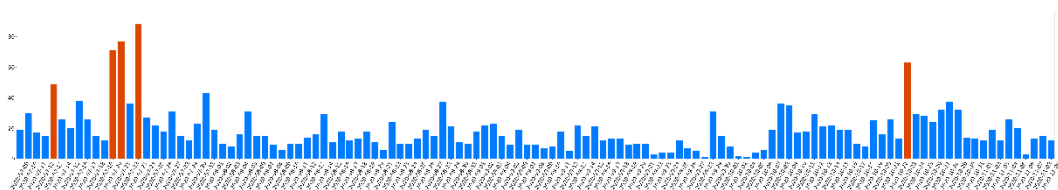
(a) Temporal evolution of user activity on Twitter for SwissCovid (CH) (2324 tweets)

(b) Language distribution of the tweets for SwissCovid (CH)

Figure 32: Further processing of the tweets about SwissCovid (CH), harvested between 09/07/2020 and 12/11/2020

(a) Temporal evolution of user activity on Twitter for Erouska (CZ) (2124 tweets)

Figure 33: Further processing of the tweets about Erouska (CZ), harvested between 09/07/2020 and 12/11/2020

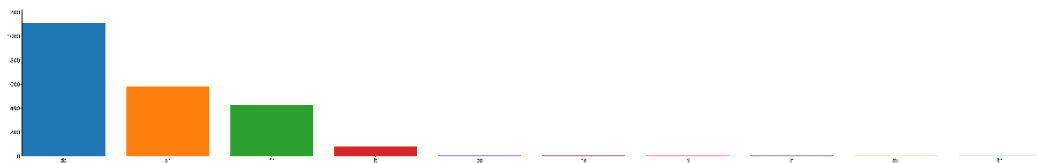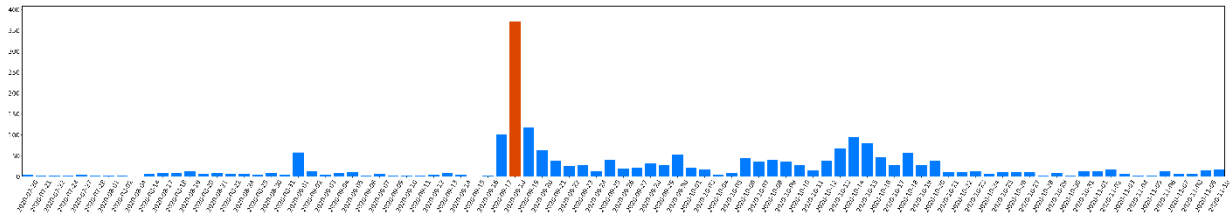We also performed sentiment analysis using a sentilexicon rule-based classifier in the tweets in English (81469 tweets) to get the overall feeling of the tweets about the most popular apps on Twitter. The results in absolute numbers (in the scale strongly negative – strongly positive) are presented in Figure 34 while the normalised sentiment for the tweets about each of the apps is shown in Figure 35.
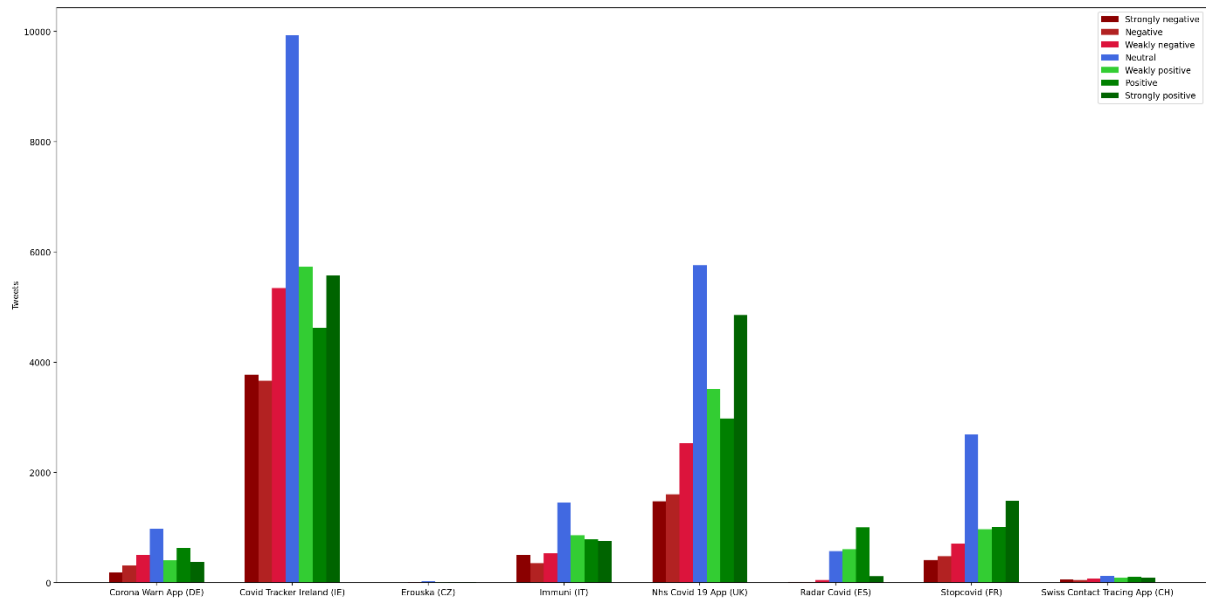

Figure 34: Sentiment analysis for the tweets in English about the popular European contact tracing mobile apps, harvested between 09/07/2020 and 12/11/2020

Figure 35: Normalised distribution of the sentiment for tweets in English about the popular European contact tracing mobile apps, harvested between 09/07/2020 and 12/11/2020

5   Early findings

We learned many lessons while carrying out the work presented above since April 2020. Some central takeaways are listed below.

Early findings from the technical work:
- Using the search APIs for app stores we gain the experience of searching available apps from the two most used stores for mobile apps, based on a specific topic. As we used different technology for each of the stores, some fine tuning needed to be done at the beginning – concerning the key terms used to retrieve the apps (e.g. adding more key terms we obtained a more concrete list of interesting apps).
- Both the APIs have some limitations in the number of requests – iTunes Search API is limited to approximately 20 calls per minute, while for google-play-scraper we experienced some blocking of the IP address - was solved by creating a repetitive procedure during the day, leaving some time slots between the requests.
- For google-play-scraper we experienced a change in the RESTful APIs – constant monitoring needs to be done (usually solved by downloading the latest version of the Node.js module), while on the other hand we found the iTunes Search API stable.
- By default, the search API results do not provide all the descriptive attributes that we were interested in, and some further requests need to be done based on the obtained list of apps (e.g. privacy URL or iOS apps, permissions for Android apps).
- After obtaining the list of apps from both stores, manual work needs to be done for their matching, since the stores are not using the same app id and usually, the apps are not named the same (the reason may be the distinctive character limitation on the stores).
- Tweet analysis and the resulting hashtag networks have given us some visual clues of relations among topics related to COVID-19 mobile apps. The subsequent sentiment analysis has shown that the relevant debates were polarised (there was strong sentiment polarity). It also showed us that there was much more attention in countries who faced hard the COVID-19 crisis (such as Italy, with the Italian contact tracing app attracting the highest attention in Twitter among the EU contact tracing apps, and the Norwegian one being the least mentioned one). Not surprisingly, most of the tweets for each app were in the official language of the country covered by it. This introduces some bias in sentiment analysis, since the sentiment analysis libraries available for each language are different.
- Monitoring media through the EMM provides a useful tool for understanding the propagation of information on apps. Reusing a controlled list of keywords which is across channels (e.g. for social and traditional media outlets) allows for comparison of the information. A shortcoming of such an approach is the bias of the resultant information introduced by the languages that are used.
- We observed that, when there is attention in the news about a contact tracing app (identified using EMM), there is also activity about this app in social media (with a delay of up to two days).

Early findings from the methodology that we applied:
- It is useful to combine information from different information channels, and the exercise that we initiated opens multiple avenues for further exploring COVID-19 related apps, and their evolution over time. We focussed our work and decided to concentrate in baseline research. Ideas for future activities are provided in the following section.
- Results from automatic (objective) processes can be combined with the findings of manual (subjective) work. However, to harmonise results coming from different viewpoints and approaches, we rely on cross-checking (peer reviews) of analysis results by more than one researcher. Also, meetings to discuss the definition of the attributes while the analysis is ongoing are a crucial factor.

- It is challenging to define attributes, and app categories in a fluid context, new features and functionalities were emerging while we were in the process of analysis the apps. Currently, a few publications are being published that might provide useful conceptual tools for future data collections and analysis[1].
- The manual analysis with many people is both a strength and a challenge of the approach we followed for the manual analysis of the mobile applications on the app stores. We must acknowledge the shortcomings of using attributes with a subjective dimension. Also, the actual meaning of which app is interesting at a given moment in time changes, for example, contact tracing apps caught our attention in the early phase and until summer 2020, whereas we found emerging apps to deal with recovery scenarios more interesting over time.

Early findings from the analysis of COVID-19 related apps:
- As the first case of COVID-19 cases started in China in early December 2019, followed by the first cases in Europe in the second half of January 2020, and declaring the global health emergency on 30th January 2020, the actual emergence of COVID-19 related apps accelerated in April 2020.
- The COVID-19 crisis led to the development of many different apps, much more than the contact tracing apps that are prominently present in the news and on social media. We now have a rich landscape of COVID-19 related apps available, and they are highly diverse across countries. Different clusters of functionalities can be spotted, but multiple practices emerge in terms of addressing quarantine management, mobility, etc.
- The public sector, i.e. local, regional and national governments, is by far the main provider of COVID-19-related apps (although most of the times these apps were formally developed by companies contracted by government).
- Sharing of personal data seems often not regulated by clear privacy policies, especially for apps released in countries outside the EU. This was indicated when analysing the text provided in the app description but would need to be verified by installing and checking/completing the attributes from a user experience perspective.
- Almost each country, especially in the EU, adopted its own contact-tracing app. Most of these apps are based on the Bluetooth technology to exchange data in a fully anonymous and privacy-respectful way. High initial interest was observed across the multiple channels which decreases over time (which means a communication campaign is critical).
- The geographic distribution of offers is highly diverse, some countries (such as India, Brazil and the USA) provide a high number of apps, but also provide different apps with similar functionalities for different cities or regions. We did not spot this general trend in European countries.
- The functionalities that the COVID-19 apps provide change over time. Whereas many apps focussed on information provision about regional situations and training (e.g. how to wash hands) early on, we whiteness a peak of contract tracing apps over the summer of 2020, followed by an increase of apps that support re-entering to schools, work, or online records of test results. Logically, the countries that were hit earlier by the crisis undergo this evolution earlier – as compared to those which were affected later.
- We also see signs of a geographic distribution in the app provisions between both app stores, which might be explained by the popularity of iOS, compared to Android and other competitors per country.

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[1] See, for example, Gasser U, Ienca M, Scheibner J, et al. (2020) Digital tools against COVID-19: taxonomy, ethical challenges, and navigation aid. The Lancet Digital Health 0(0). Elsevier. DOI: 10.1016/S2589-7500(20)30137-0.

6 Outlook to future work

The work presented in this report provided us with first insights about the diversity and evolution of COVID-19 related mobile applications. In addition to the lessons that we already learned (see also Section 5), we see several opportunities to build on our initial findings and to gather more scientific knowledge about emerging solutions, their impact, and their differences.

In the short term, we intend to extract more descriptives from the current dataset – including examples, such as, graphs about the involvement of a health authority, the presence of a clear privacy policy, etc. Also, a deeper analysis might be applied, for example, normalising the number of user ratings for apps based on the number of downloads and/or population of the countries the apps are functioning. We will benefit from existing visualisations. Examples might include the overlaying of the type of application on the application publishing timeline, to get a better view on the requirements' landscape.

We also want to improve our understanding of the differences between COVID-19 apps released in EU and non-EU countries by analysing different attributes. For instance, the analysis of app permissions (aggregated by country or EU vs. non-EU) might return interesting results. Such a work might, for example, reveal that apps outside the EU required a higher number of permissions because they collect more data - such as, geographic location when the app is in use, location all the time, microphones, cameras. We could also investigate the kind of provider involved or the functionality category of apps to see if there are differences.

For the longer-term research, we see value in investigating the following areas.

- Contextualize the apps' privacy features within the broader data infrastructure of the apps. **Examine the privacy features of the apps (based on manually and automatically retrieved attributes - such as** ClearPrivacy Policy for the former, and app permissions for the latter - in conjunction with the kind of provider and the country of origin (in Europe) of both contact tracing apps and apps with other types of functionalities. A recent research[2] (Albright, 2020 cited in Greenberg, 2020) has shown that apps that offer only information are nonetheless requiring permission to access several personal data (they are doing so to a larger extent than contact tracing apps, at least those released in EU). Therefore, we can examine such technical dimensions of COVID-19 apps pertaining privacy contextually within the broader data infrastructures, which is defined by the actors involved (providers), the app functionalities, and the deriving data flows. Also an investigation of the evolution of interoperability efforts between the contact tracing apps in the EU would be worth pursuing.
- Examine the partnerships and consortia behind COVID-19 related apps, between private and public and other parties in general. This way we could support narratives of modernising the public sector, enabling ecosystems with different players. Particular attention might be taken in respect to the involvement of **health authorities in** the apps. A recent publication[3] highlighted that health authorities are the most trusted kind of provider by citizens in the US. Which health authorities are involved in COVID-19 apps for which kind of apps? To what extent the health authority involvement matters for the total number of downloads (weighted for country's population), ratings, or clear privacy policy?
- Investigate user ratings and comments for their implications on uptake. One of the reasons – probably the primary one – for an app to be much rated or commented in the app stores is the lack of the expected functionalities (i.e. the presence of many reviews usually indicates the presence of negative reviews). This work has only marginally analysed the single user comments associated to the ratings. Bad ratings and negative reviews express also the likelihood that an app is abandoned after it is downloaded. While surveys can inform about citizens propensity to use COVID-19 apps, the analysis of ratings could be an

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[2] Albright 2020, cited in Greenberg 2020

[3] Hargittai, E., Redmiles, E. M., Vitak, J., & Zimmer, M. (2020). Americans' willingness to adopt a COVID-19 tracking app. First Monday.

indicator of the success of a particular app (or of a set of apps with certain features) after it has been downloaded.

- Explore peoples' acceptance of apps, especially related to data handling. Overall, users' ratings are informative of citizens satisfaction and trust, or lack of thereof, for the apps. It is already clear that many concerns are raised by users about the way the apps (do not) ensure their privacy, although this should be ensured according to the content of the existing privacy policy. Further work is thus needed to analyse user perception of COVID-19 related apps. The analysis of ratings and bad reviews is also a way to include the voice of users/citizens into the debate on contact tracing apps, which could challenge the "solutionism" discourse adopted by technology developers[4]. Again, particular emphasis might be put to analyse the EU context. It could be interesting to try to compute apps' scores (e.g. average/median scores) by country/EU-nonEU/providers/functionalities. Depending on the results, it would also be worth exploring whether the public debate and the involvement of EU in providing guidelines has shaped the development of COVID-19 apps in Europe.

- Understanding the role of Apple and Google in mediating data flows in contact tracing apps. We could focus on European contact tracing apps and examine how many are based on the Apple/Google interface for proximity tracing, and then conduct a qualitative investigation that goes more in depth in a subset of those apps. The apps selected for the qualitative investigation include both apps that are based on Apple/Google and those that are not. The methods can include content analysis of reviews and ratings, analysis of press coverage for those apps (EMM), or sentiment on Twitter. In the discussions we can reflect about the role and power of the Big tech in the European COVID-19 apps ecosystem.

- Geographic analysis of tweets. Regarding Twitter, there is a potential to extract place names from the tweet text from the profile information of the Twitter users using Natural Language Processing (NLP) and deep learning (ML techniques). From the tweet text it is possible to extract countries, NUTS (Nomenclature of Territorial Units for Statistics) levels or cities that are mentioned by the tweets, create geolocalised hashtag networks, as well as geolocalised topic, keyword and interactive web maps. From the user profiles it is possible to create an interactive web map where we can display the interaction between users (tweet, retweet, likes etc). This could be used to develop an oriented network where each node represents a geolocalised Twitter user and the arrows the interactions to other Twitter users. These two options can also be enriched with additional analysis, for example a "sentiment map", where we can detect the opinions about a topic in a specific area. The sentiment analysis in this case should be implemented considering a multi-language domain, using pre-trained models, such as, BERT, Roberta, ELECTRA, (transformers) and fine-tune these to adapt to our context and/or task. It would also be interesting to identify (as future work) the level of between-ness centrality of the negative/positive nodes and their roles in the network.

[4] Morozov, E. (2013). To save everything, click here: The folly of technological solutionism. Public Affairs.

Appendix A – Technical details about the app stores

A.1 Details about app store monitoring

There are two main app stores for mobile devices, App Store and Google Play that we decided to monitor for releases of new mobile apps concerning the COVID-19 pandemic as well as for the updates of these apps.

There are different sources and tools for fetching the metadata about mobile apps, including both free services and solutions based on APIs via flexible queries which are charged after a trial period (with limited queries, usually limited to a US store like, for example, SearchMan).

One of the free services provided by Apple is the iTunes Search API which allows to search content within the iTunes Store, App Store, iBooks Store and Map App Store, whereas there are no official REST services provided to look-up the mobile apps on Google Play store; for this reason, we opted to use the free Node.js module "google-play-scraper".

The data are retrieved daily and analysed once a week, using the ETL tool FME.

A.1.1 Monitoring the Apple App Store

In order to retrieve the descriptions (metadata) of COVID-19 related apps from Apple's App Store, we decided to use the free iTunes Search API, which allows to search for content within the iTunes Store, App Store, iBooks Store and Mac App Store. The search can be performed for a variety of content, including apps, iBooks, movies, podcasts, music, music videos, audiobooks, and TV shows. Query formulation is based on terms of interest and country codes of the store(s) that will be searched.

Since the Search API is limited to approximately 20 calls per minute, the automatic procedure is called with a delay of 3 seconds between calls.

The search terms that were used for retrieving all media types that are software (apps) are the combination (pairs) of two terms: "covid" and "coronavirus"; "sars-cov-2" and "coronavirus"; and "corona" and "coronavirus" with the maximum number of items in the result set to 200 for each country.

The combination of terms was used since for a query using just one term the outcome would result in a list of generic apps not always connected to COVID-19.

Below is an example of the query formulated for software (mobile apps) with the terms "sars-cov-2" and "coronavirus" in the Italian App Store where the used country code is "it" (the default value is "us" – United States). Since the default number of result items is 50, in the aforementioned query always uses the maximum number of search results which is 200.

Using more query terms resulted in getting more relevant mobile apps for each country store. Moreover, as some mobile apps were not identified using the above-mentioned query, the Search API was also used for collecting metadata about mobile apps that were identified on Google Play and then matched to existing ones on App Store. In that case a specific lookup request is done searching the App Store by the trackId value.

An example of lookup request for the app "COVID Coach" is available here.

Since we are interested in retrieving the privacy policy link, when this link is available for a mobile app, another API is used on App Store, which specifies the iTunes trackId and last version of the app of interest.

As an example, the request of the privacy policy URL available for the App with the iTunes trackId 1504705038 ("COVID Coach") and app version number "1.4" is available here.

A.1.2 Monitoring the Google Play

In order to retrieve the metadata of COVID-19 related apps from Google Play, we used the Node.js module "google-play-scraper" available for [download from GitHub](#).

The method used for identifying the mobile apps from Google Play is "search", which retrieves a list of apps that result from searching a (set of) given term(s). The search terms used are: "corona covid sars-cov-2" and "corona covid sars-cov-2 symptoms track virus social isolation self-diagnosis" and we are using the two-letter country code to retrieve the application in the specific country. In the same way as for App Store, the maximum numbers result items has been set to 250.

```
var gplay = require('google-play-scraper');
 gplay.search({
 term: "corona covid sars-cov-2",
 fullDetail: "yes",
 num: 250,
 country: "it"
 }). then(console.log, console.log);
```

In the same way as for App Store, we searched for detailed data of specific Android apps when they were identified on App Store and not on Google Play, with the "app" method of the Node.js module, which is taking as input the appId.

Below is an example, for retrieving all details about the application "Immuni" with appId "it.ministerodellasalute.immuni":

```
var gplay = require('google-play-scraper');
gplay.app({
        appId: "it.ministerodellasalute.immuni"
}). then(console.log, console.log);
```

We faced IP blocking during the lookup procedure for Google Play after a certain number of consecutive requests (e.g., same terms used for different countries) because of the Google Play throttling limit. To overcome this, an automated lookup procedure for Google Play has been scheduled to run in different time frames (at 20:00, 21:00, 22:00, 0:00, 2:00 and 4:00), depending on the terms and the country list, while the specific app lookup runs three times every day (at 3:00, 5:00 and 23:00).

A.2 Overview of the attributes captured for each mobile app

We provide here the full list of the mobile app attributes, both for the values that are automatically retrieved from the stores and the values that are decided after manual analysis.

Table A.1 shows the overview table attributes that resulted from the store lookup, as well as their mappings to the attributes of the Google Play and the App Store. The attributes indicated with * are the attributes that are generated in the procedure that automatically processes the information retrieved.

Overview table	Google Play attributes	App Store attributes
Status*		
storeName*		
appId/trackId	appId	trackId
title/trackName	title	trackName
released/releaseDate	released	releaseDate
version/version	version	version
updated/currentVersionReleaseDate	updated	currentVersionReleaseDate

Table A.1: Attributes retrieved from the app stores

Table A.2 shows the attributes with values that are added after manual analysis.

Attribute name	Values	Description
analyser	text	Name of the person who did the analysis.
analysisDate	text	Date of the analysis.
interestingApp	yes/no	A yes/no value, indicating if an app is interesting for more in-depth analysis according to the focus of our study. Criteria for flagging an app as interesting are: it is EU-based, it offers contract tracing functionalities, it includes peculiar data-sharing functionalities (e.g. particular user data is shared with a third party).
notes	text	Relevant information about the app.
comments	text	Internal comments for analysis.
providerCategory	One of the following values: non-profit organization; community; technology company; health company; other type of company; university(ies) or research centre(s); international organisation; local/regional government; national government	The type of organisation that distributes the app.

If it is a health authority, use 'local/regional government' or 'national government' and mark the health authority in the attribute 'healthEntityInvolved'. |

healthEntityInvolved	One or more of the following values: Health authority; Health facilities; Medicine Research Institute(s) University(ies); Consortium; No; NA	Indication if a health authority is/has been involved in the development/distribution of the app and/or use of data collected with the app.
EU	One of the following values: Yes; No.	Indication if the app is released in an EU country.
geographicCoverage	List of ISO 3166 – alpha 3 country codes	Countries where the app is available and functioning (according to its documentation).
appCategory	One of the following values: COVID-19 specific; COVID-19 influenced; health-generic; other	Category of the app, according to the "Framework of app functionalities".
appFunctionalityCategory	List containing one or more of the following values: expert support; information provision; personalised support without data sharing; information exchange; contact tracing; notifications; lockdown management; other-health; other	Category of the app functionality, according to the "Framework of app functionalities".
appFunctionality	List containing zero or more of the following values: monitor overall situation; manage test; recruitment; telemedicine; help in self-isolation; training; statistics; prevention; medication; news; access to health services; self-diagnosis without data sharing; symptoms monitoring without data sharing; risk assessment without data sharing; self-diagnosis with data sharing; symptoms monitoring with data sharing; risk assessment with data sharing; manage self-isolation; communication with a doctor; proximity tracking; continuous location sharing; occasional location sharing; sending notifications; sending instructions; mobility for citizen in lockdown; exit management; mobility checking	App functionalities, according to the "Framework of app functionalities". This is not valid for the "other" app category.
typesOfPersonalData	List containing zero or more of the following values: Proximity; Location as province/region; Location as GPS/cell tower data; Health status; Positive status; Other	Type of personal data collected on the app. [If Location as GPS/cell tower data is optional in a contact tracing app (because it collects proximity data), we should add a comment: "GPSoptional"].

clearPrivacyPolicy	One of the following values: Yes; No; NA	Indication if the app clearly communicates what information it collects and how it processes it.

Table A.2: App attributes with valued added after manual analysis

Appendix B – Keywords used with Twitter and the European Media Monitor

The keywords we used for filtering both EMM news and tweets are listed in Table A.3.

smartphone
app
application
mobile phone
mobile phone operator
tracking
data
movement
GDPR
hackathon
technologies
telecom
telco
mobile application
privacy
personal data
location data
geospatial/geograhic/spatial position
geospatial/geograhic/spatial location
contact tracing
trace
surveillance
anonymized
voluntary
monitoring
data collection
proximity

Bluetooth
BLE
pepp-pt
dp-3t

Table A.3: Keywords used for filtering both EMM news and tweets