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# Data Visualization and Analytics Tools for Enhanced Covid-19 Communication – A systematic Review

**Rumiza Shaikh[1], Shweta Pawar[2], Renuka Bhanage[3], Rupali Gajare[4]**

Graduate Student, Department of Computer Engineering, Dhole Patil College of Engineering, Pune, India[1]

Graduate Student, Department of Computer Engineering, Dhole Patil College of Engineering, Pune, India[2]

Graduate Student, Department of Computer Engineering, Dhole Patil College of Engineering, Pune, India[3]

Graduate Student, Department of Computer Engineering, Dhole Patil College of Engineering, Pune, India[4]

**Abstract**: COVID-19, an infectious disease caused by the SARS-CoV-2 virus, was declared a pandemic by the World Health Organization (WHO) in March 2020. By mid-August 2020, more than 21 million people have tested positive worldwide. Infections have been growing rapidly and tremendous efforts are being made to fight the disease. In this paper, the authors attempt to systematize the various COVID-19 research activities leveraging data science, from statistics, modeling, simulation, and data visualization-that can be used to store, process, and extract insights from data. In addition to reviewing the rapidly growing body of recent research, the authors survey public datasets and repositories that can be used for further work to track COVID-19 spread and mitigation strategies for authenticity and comparison purposes. As part of this, they present a bibliometric analysis of the papers produced in this short span of time. Finally, building on these insights, they highlight common challenges and pitfalls observed across the surveyed works.

**Keywords**: Coronavirus, COVID-19, Data Science, Data Visualization, Modeling, Pandemic, Simulation, Statistics

## I. INTRODUCTION

The deadly impact of COVID-19 is driving a massive amount of research that aims at understanding the various characteristics of the pandemic. Data visualization or information visualization always plays a key role in scientific analysis. A good visualization can represent inherent trends in data that may not otherwise be visible from raw numbers. The recent COVID-19 pandemic poses new challenges to data scientists, too, for its vast and rapid spread and significant economic impact. It has forced the scientific, medical, and public health communities to innovate on a scale not seen in modern human history. Charts and graphs have helped communicate information about infection rates, deaths, and vaccinations. In some cases, such visualizations can encourage behaviors that reduce virus transmission, like wearing a mask. Indeed, the pandemic has been hailed as the breakthrough moment for data visualization. In the current era of big data, a huge amount of data has been generated and collected from a wide variety of rich data sources. Embedded in these big data are useful information and valuable knowledge. Knowledge discovered from these epidemiological data helps researchers, epidemiologists and policy makers to get a better understanding of the disease, which may inspire them to come up with ways to detect, control and combat the disease. Data visualization has arguably been the star of coronavirus pandemic coverage. From early graphics urging us to flatten the curve, to John Burn-Murdoch's Financial Times charts, to regularly updated dashboards like the Johns Hopkins COVID-19 dashboard, the authors have been inundated with visual interpretations of the pandemic data. The authors have reviewed techniques used by authors in their work and underlined some trivial as well as significant inconsistencies which they have explained our views on. They have also mentioned below, some examples of visual storytelling and scrolly telling about the coronavirus pandemic that they would like to add to the chain of data visualization techniques used by authors of works published prior to ours. This paper addresses on recent studies that apply ML and AI technology of Data Visualization towards augmenting the researchers on multiple angles. It also addresses a few errors and challenges while using such algorithms in real-world problems. The paper also discusses suggestions conveying researchers on model design, medical experts, and policymakers in the current situation. It discusses ways the pandemic has accelerated digital transformation exponentially and suggests how analysis can be augmented by accessing additional COVID-19 data sources and by learning how to visualize COVID-19 data responsibly. A selective assessment of information on the research article was executed on the databases related to the application of ML and AI technology of data visualization on Covid-19. Rapid and critical analysis of the three crucial parameters, i.e., abstract,

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methodology, and the conclusion was done to relate to the model's possibilities for accurate representation of the various analytical metrics of the SARS-CoV-2 pandemic and its outbreak.

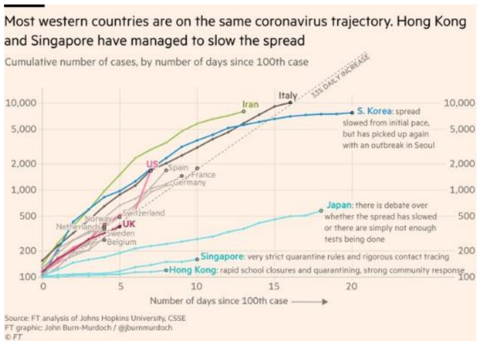


*Figure 1:* John's tweet on log scale (and several hundreds of comments later) March 11, 2020 (Image courtesy: Jason Forrest-How John Burn-Murdoch's Influential Dataviz Helped the World Understand Coronavirus)

## II. DISCUSSION

***Why data visualization has played a prominent role in pandemic coverage***

Fundamentally, data visualization is basically visualizing data. Usually the data is quantitative, and the goal is to show it graphically. One of the main ways that data visualization creates insight is by creating comparability between data. At its core, data visualization is a way to communicate and make sense of information. As people going through a very challenging global health crisis, the authors are craving narratives and information to help us understand what is happening. This is why they see the popularity of graphs that compare COVID-19 data from different countries. Data visualization has been critically important in communicating and convincing them to act. Some of the early graphics that became widely shared and influential during the initial stages of the pandemic in North America and Europe urged people to do their part by succinctly explaining the concept of 'flattening the curve'.

***The challenges of visualizing the uncertain***

Behind every chat, graph, or model that we see is a complex set of choices and tradeoffs that the author has made to get to a final report. So much about the case data and even the deaths data has so much uncertainty around it. The authors have an expectation these days that data is instant, but the reality is that case reports for COVID-19 data move through a somewhat manual process. For example, there's a lag from when a test is taken to processing the test in a lab to when the result gets recorded in the official counts in a local or national repository. While many graphs emphasize comparability, definitions are inconsistent across states and countries, for example, what counts as a death attributed to COVID-19. Cases are also a function of the rate of testing that is happening, which varies widely in different countries. In addition, they have to consider data quality, when at every level where you are aggregating data, small data quality issues at the lowest level get compounded as you keep aggregate. This is why the trusting the data at the local administrative level first is a common notion. Perhaps the biggest challenge for data visualization designers during the pandemic is how quickly the data changes and how much uncertainty we are dealing with. Part of the comfort and popularity of data visualizations during this time is the perception that it makes us more certain, and it makes the data seem more certain. Listed below are a few repetitive challenging setbacks occurring in most of the published works the authors reviewed for this paper.

***Unreliable Datasets***

Collecting and aggregating global data in a rapidly changing environment, such as during a pandemic, is obviously very tricky. None of the available datasets should therefore be considered an 'absolute truth', as minor errors are bound to happen. Such errors can be related to reporting difficulties or contradicting sources, or differences and shifts in methodology undertaken by the data collectors, but can also be due to minor errors such as typos. Some datasets may appear to lag behind by the official government datasets, possibly because their reports are published at specific timings which don't match accurately with government reporting timings. Also, these datasets might miss the same update due to not being updated on particular dates. They may also appear to have a typing error in them. This causes a small overlap making it difficult to accurately compare data and analyze trends. Several of the datasets also fail to include diverse sets of patients, putting some of the models at high risk of contributing to biased and unequal care for Covid-19, which has already taken a disproportionate toll on Black and Indigenous communities and other communities of color.

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That risk is clear in a research. After analyzing dozens of Covid-19 prediction models designed around the world, the authors concluded that all of them were highly susceptible to bias. These shortcomings raise an important question about whether the divided efforts come at the cost of a more comprehensive, accurate model, one that is built with contributions from all of the research groups currently working in isolation on their own algorithms. Such datasets used by authors to compile their thesis and research work draws focus and credibility to their proposed methodology and execution rather than to the authenticity of the data they put forth through their work.

| | World Health Organization | John Hopkins University | Our World in Data | Belgian government |
|---|---|---|---|---|
| March 1 | 1 | 2 | 1 | 2 |
| March 2 | 1 | 8 | 1 | 8 |
| March 3 | 8 | 13 | 8 | 13 |
| March 4 | 8 | 23 | 8 | 23 |
| March 5 | 23 | 50 | 23 | 50 |
| March 6 | 50 | 109 | 50 | 109 |
| March 7 | 109 | 169 | 109 | 169 |
| March 8 | 169 | 200 | 169 | 200 |
| March 9 | 200 | 239 | 200 | 239 |
| March 10 | 239 | 267 | 239 | 267 |
| March 11 | 267 | 314 | 267 | 314 |
| March 12 | 314 | 314 | 314 | 399 |
| March 13 | 314 | 559 | 314 | 559 |
| March 14 | 599 | 689 | 599 | 689 |
| March 15 | 689 | 886 | 689 | 886 |
| March 16 | 1 085 | 1 058 | 1 085 | 1 058 |
| March 17 | 1 085 | 1 243 | 1 085 | 1 243 |
| March 18 | 1 486 | 1 486 | | 1 486 |
| March 19 | | | | 1 795 |

*Figure 2:* Comparison between different data sources of the reported total number of confirmed COVID-19 cases in Belgium between March 1 and March 19, 2020 (Image courtesy: Koen Van den Eeckhout - Data visualization in a time of pandemic)

***Logarithmic scales map exponential growth well but are very difficult for people to understand and may sometimes mislead***

Many researches portray information about the number of COVID-19 cases and deaths using a logarithmic scale graph. At first sight, this seems sensible. In fact, many authors defend their decision by showing how much better these charts are in conveying information about the exponential nature of the contagion. We can assume that if the number of active infections follows a Gaussian-shaped profile, the number of new infections and the number of deaths will also follow Gaussian profiles. If we plot cumulative data, such as the total number of confirmed cases or the total number of deaths, this will follow an S-shaped cumulative function profile — the integral of the Gaussian function. Therefore, while the logarithmic group predicts more deaths in the short term due to the higher anchor, the linear group expects the crisis to last longer. Consequently, the linear group is more worried about the health crisis, while anticipates to wear masks less often in order to ration them. Unlike the people who see the graph on a logarithmic scale, the people exposed to a linear scale graphs tend to form their preferences based on information that they can understand better. This is a strong enough reason to suggest that researchers should try to describe the evolution of the pandemic using a graph on a linear scale, or at least they should show both scales.

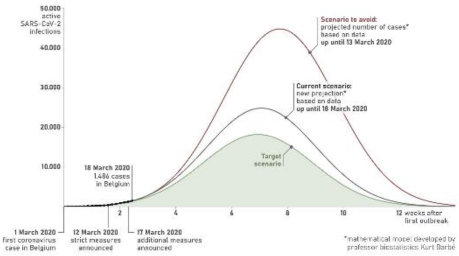


*Figure 3*: Different scenarios for the coronavirus spread in Belgium, as modeled by professor Kurt Barbé (March 18, 2020).

***Mapping issues***

Maps have been heavily used in research visualizing Covid-19. One of the most common issues encountered when creating data maps is the impact of population and population density. If we simply color a map according to the presence of a certain parameter, we can easily mask the fact that we are actually looking at a map of an underlying *different* parameter, such as population density. Furthermore, maps have their own challenges, such as whether to use a choropleth or heat map, where areas are coloured or shaded based on data, or symbols centered on a location, such as circles, the size of which is based on data. What authors choose depends on the question they are trying to answer for their readers. However, choropleths fail to represent proportional symbolized data when constituent areas vary a lot in

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size, with geographically tiny countries such as Singapore being near-invisible on a global scale. The varying shades along large intervals often seem to overlook those along small intervals which again raises questions on the visualization authenticity.


*Figure 4*: Dangerously misleading Mapwork

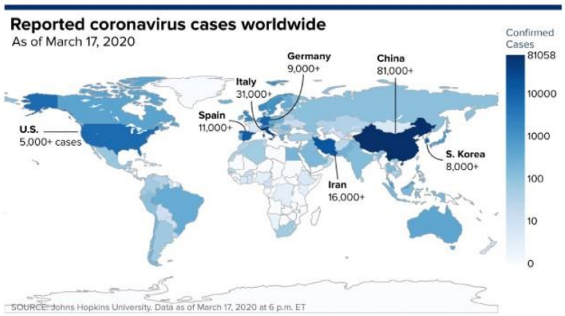


*Figure 5*: Choropleth map of reported coronavirus cases worldwide as of March 17, 2020 (CNBC).

***Tabular Data Glitches***

Countries use different systems and classifications for recording deaths by COVID-19. These differences may refer, for example, to whether a deceased patient with a severe comorbidity and a confirmed SARS-CoV-2 infection is recorded as having died from COVID-19 or from the comorbidity. Published researches have failed to touch these possibilities. Further, countries have changed their standards regarding when a death is counted as a death by COVID-19 over the course of the pandemic. This has led to concerns that countries might either be undercounting or overcounting the deaths by COVID-19. Reporting lags of the data represent another common pitfall when studying the latest developments of the coronavirus situation. Reporting lags occur in tables used by numerous researches, for example, when decentralized offices and institutions do not meet their deadlines for reporting their data to a national agency that then processes and publishes the collected data. Reasons for such non-compliance can be the high workload of local offices during an epidemic or local bottleneck in testing capacities. Reporting lags become visible only when updates and revisions to the data are published. Statistics Sweden (2020), the Swedish government agency responsible for producing official statistics, has been very transparent regarding the expected reporting lags and the necessary revisions to the reported data on daily deaths in Sweden. Most often, the data collected and analyzed in the context of the coronavirus pandemic do not represent random samples of the underlying population. The same applies to most data being utilized in the social sciences. A consequence of using selected samples is that the insights obtained by means of statistical analysis cannot be trusted to generalize to the overall population. The issue of generalizability as observed in many studies is even more relevant regarding the various serological samples that are being collected and analyzed, as they are intended to inform on the true spread of SARS-CoV-2 among the population. Recruitment into these samples often raises concerns about selection: on the one hand, voluntary participation might attract individuals that suspect they may have experienced an infection with SARS-CoV-2 with mild symptoms.

| NETHERLANDS | | | ITALY | | |
|---|---|---|---|---|---|
| Date | Cases | Deaths | Date | Cases | Deaths |
| Mar 16 | 1 413 | 24 | Feb 29 | 1 049 | 29 |
| Mar 17 | 1 705 | 43 | Mar 1 | 1 577 | 41 |
| Mar 18 | 2 051 | 58 | Mar 2 | 1 835 | 52 |
| Mar 19 | 2 460 | 76 | Mar 3 | 2 263 | 79 |
| **Mar 20** | **2 994** | **106** | **Mar 4** | **2 706** | **107** |
| Mar 21 | ... | ... | Mar 5 | 3 296 | 148 |
| Mar 22 | ... | ... | Mar 6 | 3 916 | 197 |
| Mar 23 | ... | ... | Mar 7 | 5 061 | 233 |
| Mar 24 | ... | ... | Mar 8 | 6 387 | 366 |
| Mar 25 | ... | ... | Mar 9 | 7 985 | 463 |

*Figure 6*: Table comparing the number of infections and deaths between the Netherlands and Italy.

***Flattening the Curve***

The "flattening the curve" chart is no different to being claimed by researchers, to be a simplified tool for understanding a complex reality. Embedded within the most common versions of the chart are a few simplifying

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assumptions: 1) That the number of people infected over time will be roughly similar if the curve is flat or spiky, 2) That the severity of illness, the amount of burden people who are sick will put on the health care system will remain roughly similar over time, and 3) That the capacity of the health care system will remain roughly similar for the duration of the pandemic. There is much we don't know yet about coronavirus. But we shouldn't necessarily assume that these three assumptions are true. Countries became obsessed with flattening the curve, and it is not an easy thing to do. Flattening the curve is what every country is obsessed with, so much that they end up misleading viewers with faulty graphs. It has been observed in research works that up to a certain date the bars' height corresponded to the numbers, thereon the scaling of bars became inconsistent with the numerical differences. For an increase of x new cases, the graphs went up by x/2 units only, all in the bid to flatten the curve. Cases keep growing exponentially, and it is a bad sign. This error was skipped by numerous research works.

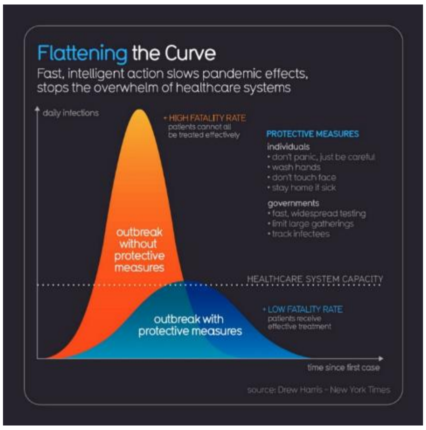


*Figure 7*: Flattening the curve visual from the Information is Beautiful COVID-19 #Coronavirus Data Pack.

## III. FUTURE DIRECTIONS

An important challenge for future developers of information visualization tools for public health is to focus not only on individual user needs and comprehension of graphics, but also to plan and develop these tools in the broader contexts of available data, existing algorithms/services, team collaboration, and inter-organizational and interdisciplinary needs. Too many software projects are developed as new information silos, resulting in redundancy of effort, failure to integrate data and tools, and challenges to training and adoption. Further, many existing systems are access-restricted, limiting their use in infectious disease epidemiology, and may not have completed (or shared) evaluations of their visualization features. Visualization tools of the future should be developed to be compatible with existing data formats and standards, and interoperable with each other. Future tools should also adapt to the increasing pressure to be open-access, allowing users from low-resource settings, academia, and industry to capitalize on the advances in surveillance and visualization technology. This level of interoperability could support more advanced features such as phylogeography (the study of genetic variation across geographic space), inference of person-to-person contact from molecular epidemiology, statistical cluster detection based on joint spatiotemporal and genomic data, integration of remote sensing and environmental data, and other tasks as users become increasingly savvy in their use of advanced analytical and visualization tools for public health.

## IV. LIMITATIONS

Although this systematic review covers a wide range of visualization tools for infectious diseases, there are two main limitations. First, many public health informatics tools, if described in manuscripts at all, may be published in non-indexed conference proceedings, and thus more recent or undersold tools may not have been retrieved. Further, systems or informatics needs assessments that have no associated publications on their visualization features (e.g., developed and used in practice only) were not readily available for our study, and systems with access-controlled content could not be assessed in context with the other tools identified here.

## V. CONCLUSION

There is no more important time for health organizations to use all of the data available to them than in a health crisis. The data can help health officials stay informed, but it can also help inform a response – where and how to intervene. As a result, the care that is being provided can improve and lives can be saved. The way that data is presented can also make a difference. Many different organizations are using visualizations of the current coronavirus that allow the data be viewed and understood more easily in order to improve the response. In this review, the authors assessed the inconsistencies with the current landscape of visualization tools developed for infectious disease epidemiology. The richness of the information offered by these data for communication and decision making are counterbalanced by difficulties in displaying, interpreting, and trusting these data sources. Several themes and challenges emerged pertaining to both individual stages as well as broader topics. Despite the different scholarly approaches of the included articles, the following themes emerged: (1) importance of knowledge regarding user needs and preferences; (2) importance of user training; integration of the tool into routine work practices; (3) complications associated with understanding and use of visualizations; and (4) the role of user trust and organizational support in the ultimate usability and uptake of these tools. A lot of people who don't practice data visualization won't know the nuances into the methodologies. They will see an official looking chart and take it as a hard fact. Herein lies the risk for both data visualization creators and consumers. The issue is around trusting data and how it can be manipulated or misrepresented. The very best visualization are the ones that force you to think about the human side of things. Data visualization is one more way for us to try to make sense of the complex, nuanced, and uncertain crisis that we are all living through. It comes with its own pitfalls, benefits and complexities.

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The Authors declare that there is no conflict of interest.

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