Internet Sectoral Overview
Number 2
August, 2020
Year 12

Use of Artificial Intelligence in Health:
Lessons learned while addressing the COVID-19 outbreak

By Edson Amaro Jr[1], Michel Fornaciali[2], Andre Batista[3], Murilo Gazzola[4], Lívia Paiva da Silva[5], Diogo F. C. Patrão[6] and Marcos Freitas Jr[7]

In the context of the COVID-19 pandemic, the need for interaction between health professionals and data analysis technologies has become more evident. The direct applications involve care scenarios (helping assign risk scores to patients in relation to the prognosis and improving medical care decisions), short-term planning (organizing teams and resources for providing care), and evaluation of public policies and macro-regional actions in the long term (applications of epidemiological models and simulations).

Each of these scenarios requires specific approaches. In health care, solutions are critical for front-line professionals and are applied when patients are in primary, secondary or tertiary care[8]. In short-term planning, tools are needed for managing teams or equipment that can be operational in up two weeks, applied in the management of hospitals, cities and states. For long-term planning, it is necessary to devise strategies for micro- and macro-regions based on adjustable scenarios, applied not only locally, but also on a national scale. On all these fronts, the goal is to use technology to prevent avoidable deaths and those resulting from complications. This is a challenge, particularly in view of the lack of resources; however, in a context such as this, data analysis technologies can help make healthcare systems more efficient, especially the work of health care teams.

[1] Neuroradiologist and superintendent of Data Science and Analytics - Big Data of Hospital Israelita Albert Einstein (HIAE) and professor at the University of São Paulo (USP).

[2] Holds a PhD and Master's degree in Computational Engineering from the State University of Campinas (Unicamp), and a Bachelor's degree in Computational Science from Unicamp. He is a data scientist on the Big Data Analytics team of HIAE.

[3] Holds a PhD in Computational Engineering from the Polytechnic School of USP and is a member of the Big Data Analytics team of HIAE.

[4] PhD student, he holds a Master's degree in Computational Sciences and Computational Mathematics from USP. He is a member of the Interinstitutional Center for Computational Linguistics of USP, and a data scientist on the Big Data Analytics team of HIAE.

[5] Graduate student in Health Management at HIAE, she holds a postgraduate degree in Project Management and Electrical Engineering with an emphasis on Telecommunications from Mackenzie Presbyterian University. She is a Telecommunications Technologist from Unicamp, and a Technician in System and Data Analysis and Processing from the Federal Technical School of São Paulo.

[6] Holds a PhD in Oncology from the Antônio Prudente Foundation (FAP/A.C.Camargo Cancer Center) and an undergraduate degree in Physics from USP. He is a data scientist on the Big Data Analytics team of HIAE.

[7] Holds a Master's degree in Information Systems from USP and an undergraduate degree in Systems Analysis and Development from the the School of Thermomechanical Technology (FTT). He is a data scientist on the Big Data Analytics team of HIAE.

[8] Primary care focuses on actions related to reducing the risk of diseases and protecting health. Secondary care is provided by hospitals and outpatient clinics responsible for providing the population with treatment in pediatrics, cardiology, and other medical specialties, in addition to ensuring the structuring of urgent and emergency services. Finally, tertiary care offers high-complexity services, represented by large hospitals and specialized clinics.

If AI models generally depend on a large volume of data, how do you deal with scarce data in the initial stage of a pandemic?

Experience in Big Data analytics at Hospital Israelita Albert Einstein

The organization of teams dedicated to the study, discussion and development of data analysis-based support tools and, in particular, Artificial Intelligence (AI) algorithms, is no easy task. The challenge is even greater when carried out in remote work contexts, in order to comply with social distancing measures imposed to curb the new coronavirus.

The Big Data Analytics group of Hospital Israelita Albert Einstein (HIAE) underwent this unique experience. Located in the city of São Paulo, this hospital treated the first case of the disease in Brazil. There were many challenges in implementing AI solutions in hospital routines, particularly the following paradoxical issue: If AI models generally depend on a large volume of data, how do you deal with scarce data in the initial stage of a pandemic? The practical aspects of forming a team to address the specific aspects of this situation, where there is not enough data or it lacks in quality, can provide insights for post-pandemic periods.

Based on an agile project management model (Hidalgo, 2019), the multifunctional Big Data Analytics team of HIAE was subdivided into squads (teams of professionals dedicated to specific tasks or projects) with profiles according to specific types of expertise. One person was designated as the focal point for intercommunication within the group, and as the spokesperson in forums to define the scope, strategy, governance and presentation of the evolution of solutions for areas that would use them.

Initiative to involve the open community: AntennaCovid

The participation of the community that deals with data processing and analysis is crucial in the context of a pandemic. For this reason, it is important to create spaces that include several fronts, such as researchers, managers and scientists (Marston et al., 2020). The management of these participatory spaces requires finding people with varied areas of education, with the sensitivity to recognize and use the different knowledge and experiences of individuals, united around the goal of creating support solutions for health professionals.

How is it possible to maintain constructive co-production in the context of a pandemic, with pressure to generate practical results in a short time? It was within this context that AntennaCovid emerged – a forum for interaction between health professionals, data scientists, machine learning engineers and mathematicians, working together to combat COVID-19. Supported by the National Education and Research Network and scheduled to exist whenever necessary, AntennaCovid was divided into various platforms to enable participants to work and share their projects – such as GitHub (github.com/antennaCovid), for sharing open-source codes; Slack (antennaCovid.slack.com), for facilitated communication, integrated with coding; and the website (antennaCovid.org), for dissemination to the public.

In addition, weekly virtual meetings are held for members to share their concerns, ideas and work. There are also roundups, scheduled as needed to discuss the development of projects and presentation of practical results. It is important to note that everything is openly disseminated on GitHub.

Therefore, AntennaCovid manages a participatory forum open to the community to increase knowledge through networking, so that everyone can put forth their goals, control their development, and interact with teams in different institutions. It is worth pointing out that various similar initiatives have been created in Brazil, some of which directly interact with AntennaCovid, underscoring the strong potential of using collaborative networking tools in the country.

Predictive solutions during care: D+0[9]

Interactions between health professionals and data analysis and machine learning technologies during provision of care serve as fertile ground for developing predictive models. It is possible to create solutions that assign risk scores to patients in relation to prognoses and improve decisions regarding the need for and intensity of medical care – essential contributions for addressing COVID-19, since early identification of high-risk patients can, for example, reduce the use of invasive mechanical ventilation (Sun et al., 2020).

In the case of new diseases, such as COVID-19, algorithms can learn patterns in reference to the interactions of the patients' characteristics that lead to both a greater risk of a positive diagnosis of the disease (Batista et al., 2020) and the evolution of the condition or even death, thereby assisting teams in making clinical decisions and allocating physical resources for more serious cases (Alimadadi et al., 2020)[10]. Therefore, the development of models to predict prognoses can provide support in medical routines for triage of patients and determining treatment, among others[11].

In a systematic review of publications in the area of health, Wynants et al. (2020) assessed the construction, evaluation and scientific dissemination processes of 66 predictive models for COVID-19. A significant number of models have been designed to predict the disease through images. The authors also identified as most commonly used predictors for diagnosing COVID-19 factors such as: age, sex, body temperature, vital signs, symptoms, blood pressure, and creatinine. Outcomes for death, clinical deterioration and length of inpatient stay have also been highlighted among prognostic models.

There have also been studies dedicated to the construction of online tools for predicting COVID-19 risk scores (DeCaprio et al., n.d.) and the development of mobile applications for diagnostic prediction of the disease based on the insertion of lab test results and patients' symptoms (Meng et al., n.d.). These studies have reinforced the important concept of data sharing in science (eScience and open data science). Other authors have shared their source codes, enabling the scientific community to know the technical specifics of the models built.

Interactions between health professionals and data analysis and machine learning technologies during provision of care serve as fertile ground for developing predictive models.

[9] Solutions for activity on the same day – "D+0".

[10] More specifically, Batista et al. (2020) presented a predictive model for COVID-19 based on information such as age and sex, as well as basic blood tests. Five supervised predictive models were built and assessed, wherein the best one (support vector machine) demonstrated that the use of lab tests is promising for diagnosing the new coronavirus. This conclusion was corroborated by subsequent studies in institutions in other countries (see, in particular, Gao et al., 2020 and Brinati al., 2020). The importance of building predictive models for COVID-19 prognoses is also confirmed in a study by Hirsch et al. (2020) on the incidence of acute renal failure in patients with the disease.

[11] Also in this regard, efforts have focused on predicting acute renal failure in hospitalized patients. The models are built from computational architectures of recurrent neural networks, particularly for long short-term memory (LSTM), discussed in Swapnarekha et al. (2020).

Both the quality of the data and its collection conditions and use in care routines are essential, so that analytical solutions will add value to the practices of health professionals.

Despite efforts to disseminate results and the resulting predictive models, it is important to note, as per Wynants et al., that these models need to undergo an external validation process before being incorporated into medical practices (Cosgriff et al., 2019). Both the quality of the data and its collection conditions and use in care routines are essential, so that analytical solutions will add value to the practices of health professionals.

Advances in the use of machine learning techniques, and an abundance of scientific publications that have presented optimistic results on how predictive models can contribute to the medical profession, open space for reflection and draw attention to the importance of good practices in the dissemination of these models. Adopting these practices enables critical analysis by peers and detailing of premises, sample selection processes, and transformations applied to the data, as well as considerations that can enhance the understanding of the scientific community and optimize the work of external validation[12].

Predictive solutions for management of services: D+15

Short-term predictions – for up to 15 days, or D+15 – have assumed different roles among the contexts and stages of progression of COVID-19. In the beginning of the pandemic, exponential growth, not just in Brazil, was noted in the number of people infected (Remuzzi & Remuzzi, 2020). At that time, it was essential to understand when there would be a change in the slope of the curve, especially for planning the physical and human resources needed for providing the best care.

Prediction models using traditional techniques that indicated linear and/or exponential growth were used during this stage (Martinez et al., 2020). Countries where the spread of the virus was more advanced were important pro xies for understanding the behavior of the curves (Barmparis & Tsironis, 2020), even allowing the initial projection of the evolution of cases in Brazil through clustering methods. Although mid- and long-term projections have been more requested by managers, mainly due to the greater impact of urgent decisions, short-term models with a simplified mathematical approach have continued to be relevant. This is because – even though seemingly contradictory – more complex mathematical models are not necessarily more reliable and do not always yield the best results (Roda et al., 2020).

Therefore, dealing with the plurality and limitations of the predictive models presented (Roda et al., 2020) requires understanding different contexts, as well as the challenges and results of various groups of researchers around the world. Examples of typical scenarios are scarcity of data (common at the beginning of a pandemic), inconsistency in the collection process, and lack of well-established parameters. Others are the adoption of varied criteria for testing infected individuals, conflicting government decisions and, specifically in Brazil, socioeconomic differences among regions, which limit the possibility of generalizing the results and are reflected in the quality of data records[13].

[12] The guideline Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD), for example, was one of the first instruments for verifying minimim requirements for the publication and dissemination of predictive models (Collins et al., 2015), and continues to be quite useful.

The intense exchanges that occurred between groups of researchers due to the pandemic resulted in learning lessons that developing predictive solutions – even if short-term, with a positive impact for managers – involves more than just mathematical approaches and requires an understanding of the contexts and limits of use. Understanding current challenges is essential for accurate interpretation of what the predictions say and for reducing risks when they are used to support decisions, especially for public policies in the health sector.

Long-term solutions: D+30 models and epidemiological cycles

Although they involve some variability, long-term predictive models are important, not only as instruments for obtaining statistics for future months, but also especially for understanding how non-pharmacological interventions, government decisions, and the natural dynamics of macro-regions are reflected in the behavior of prediction curves over the course of time. Understanding heuristically (by construction) that there is a set of projections that indicate trends with a more accentuated slope can provide relevant insights in terms of the effectiveness of actions.

Epidemiology is, by definition, the study in quantitative terms of the distribution of health phenomena and their determining factors in the population. For this reason, it is the science that uses long-term predictive models the most. In the case of COVID-19, its use focused on simulations of the propagation of the virus in 60 days or more, as well as on identifying and characterizing risk groups – crucial actions for better management of the pandemic for the sake of public health.

> Epidemiology is, by definition, the study in quantitative terms of the distribution of health phenomena and their determining factors in the population.
> For this reason, it is the science that uses long-term predictive models the most.

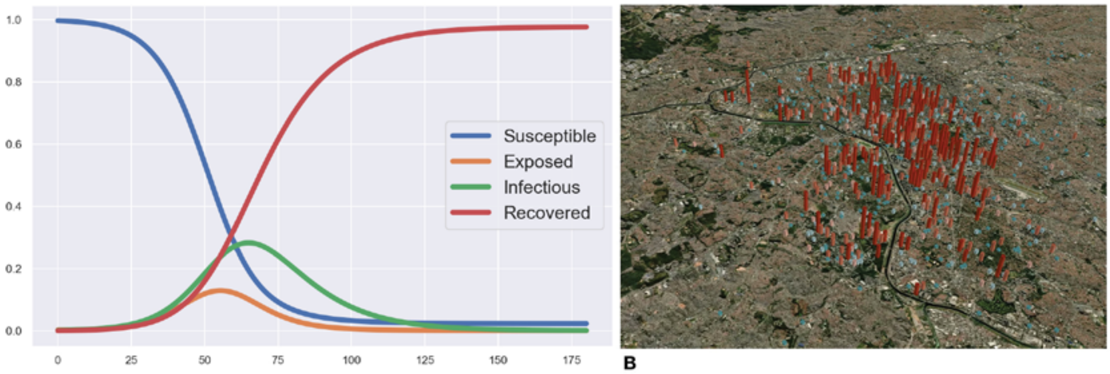
Long-term simulations

Every epidemic is the manifestation of a disease characterized by its rapid transmission, simultaneously infecting many people in the same place. Understanding the specific epidemiological cycle, from the start of the outbreak until its extinction, is a complex task, especially for new diseases. Therefore, models that describe transmission among individuals in a simplified way were used.

Among the wide range of existing epidemiological models (Britton, 2009; Chowell et al., 2016), the authors of the present article focused on deterministic compartmental models. The SEIR model was adopted, which characterizes a population in an epidemic in four stages: susceptible, exposed, infected and recovered (which includes deaths). Figure 1 shows the theoretical evolution of the disease and indicates the percentage of the population in each stage over time.

[13] Delays in reporting hospitalizations and deaths, for example, are a problem faced in many countries, with an impact on the use of techniques for updating data (nowcasting), intended to enhance the accuracy of the predictive solutions developed (Altmejd et al., 2020; Schneble et al., 2020; Puca & Buonanno, n.d.).

Figure 1 – Theoretical representation of a pandemic using the SEIR model (A) and representation of tests for COVID-19 in São Paulo on March 12, 2020 (B)



Source: Prepared by the authors.

As with all mathematical simplification, the SEIR model has limitations. Two of the more notable are overestimation of cases and dependence on strong premises related to the uniform probability of people getting infected. In the case of COVID-19, it must also be taken into account that it is an unknown disease, with few published studies and a highly dynamic context for understanding it. These complications prevent application of the model to accurately determine when the phenomena of interest will occur (the peak of the curve of infections and the end of the epidemic, for example) and what its magnitude will be (how many cases will there be at the peak of the curve and how many deaths will there be at 90 days).

To reduce technical and contextual limitations, two innovations were introduced into the models: working with multiple scenarios to identify uncertainties; and considering real COVID-19 mitigation actions to increase the assertiveness of the curves. First, attention was focused on the infection curve, since the numbers of new cases, hospitalizations and deaths are derived from it. When modeling this curve, the concept of uncertainty was incorporated through a visual illustration of various scenarios over the course of time, representing fluctuations between more optimistic and more pessimistic contexts. This approach makes users aware that the models will naturally be inaccurate, thereby preventing a literal interpretation of the figures presented in the simulations. When comparing differences between scenarios in the same model, the impacts in best-case and worst-case scenarios can be inferred, which has been successfully addressed in other studies on the new coronavirus (Lopez & Rodo, n.d.; Prem et al., 2020).

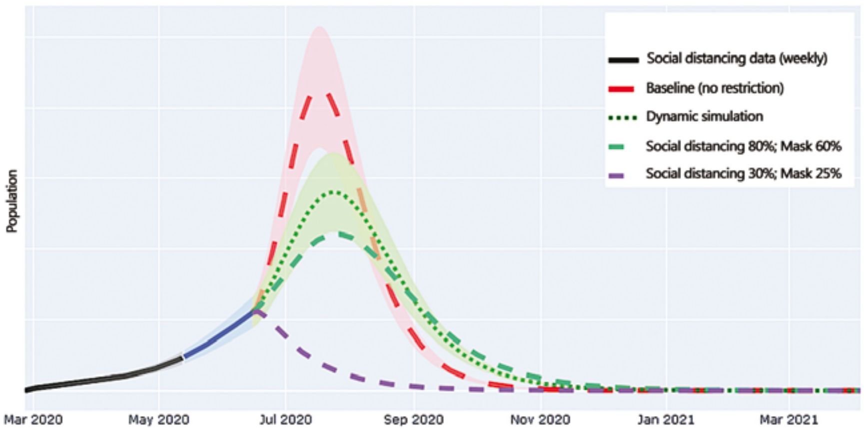
The SEIR model assumes that the entire population can be infected and that transmission of a disease occurs freely, without mitigation actions, which leads to overestimation of the number of cases. To mitigate this phenomenon, initiatives to control the spread of the virus were incorporated into the modeling. Since there are no vaccines or specific drugs for COVID-19, these measures were mostly non-pharmacological (Lai et al., 2020), such as personal hygiene and social distancing.

One of main parameters of modeling is the reproduction number (R0), which determines the transmission potential of a disease, i.e., how many new cases an infected person produces. In general, R0 is treated as a single rate over time. However, during a pandemic, a number of interventions are applied to mitigate transmission of the virus. The models in the present study sought to mathematically estimate how much each intervention and adherence to it by the population affect R0, creating a comparable R0 through scenarios.

Since the actions with the greatest impact on the mitigation of COVID-19 are social distancing (Hellewell et al., 2020) and the use of masks (MacIntyre & Chughtai, 2020), these measures were implemented to adjust the R0[14]. This resulted in a more realistic simulation, highlighting the uncertainty of the approach. Users can navigate via the simulator, creating situations of adherence to non-pharmacological interventions and comparing their effects over the long term. For example, Figure 2 compares four scenarios with different rates of adherence by the population to social distancing and the use of masks, as well as a current simulation and a scenario without any intervention (baseline) – for these last two categories, the shaded areas illustrate uncertainty.

The models in the present study sought to mathematically estimate how much each intervention and adherence to it by the population affect R0, creating a comparable R0 through scenarios.

Figure 2 – Tool resulting from a COVID-19 simulation over the long term



Source: Prepared by the authors.

In relation to understanding risk groups – a relevant task in terms of public health – the first step is recognizing who is the most susceptible to experiencing the serious effects of COVID-19. In general terms, they are elderly people and those with comorbidities (hypertension, obesity and diabetes, etc.) (Jordan et al., 2020). As the pandemic spreads, it can be seen that the higher-risk population becomes those who are the most likely to be infected and those who have restricted access to the healthcare system, i.e., poorer people and those who cannot self-isolate for various reasons, especially due to lack of formal employment and inability to work remotely.

This population was identified and geolocalized, which is an essential activity in the prioritization of regions for interventions by health managers. In

[14] Social distancing rates come from mobility estimates based on the triangulation of mobile phone antennas. Use of masks is not measured officially, so an empirical estimate of the percentage of the population that adheres to the measure is used. A mask efficiency percentage was also defined, considering the quality of the product and its incorrect use by individuals.

To analyze complex data, such as data from the health sector, it is necessary to gather information in order to understand quantitative-based phenomena for carrying out prediction, prescription or classification analyses.

addition, it is possible to target locations for constructing mass testing centers, or even defining parameters for reopening cities in post-quarantine periods. It is hoped that these interactive tools will enable managers to compare measurements; although there is no certainty as to the absolute magnitude of their effects, it is quite reasonable to consider their relative comparison.

The authors of the present study also believe that actions guided by epidemiology will generate more dynamic solutions for healthcare managers for understanding and assessing how measures adopted in the present will impact the future of the COVID-19 pandemic. Similarly, the identification and localization of vulnerable populations expedite decision-making and promote better public health management.

Data lake solutions: Organizing data from multiple sources

To analyze complex data, such as data from the health sector, it is necessary to gather information in order to understand quantitative-based phenomena for carrying out prediction, prescription or classification analyses. In view of the lack of available data at the beginning of the COVID-19 pandemic, this need became even more urgent. Each of the three main databases containing the daily figures for cases of the disease by country has a different methodology, generating differences in formatting, granularity of locations, and addresses (URLs) for recovery.

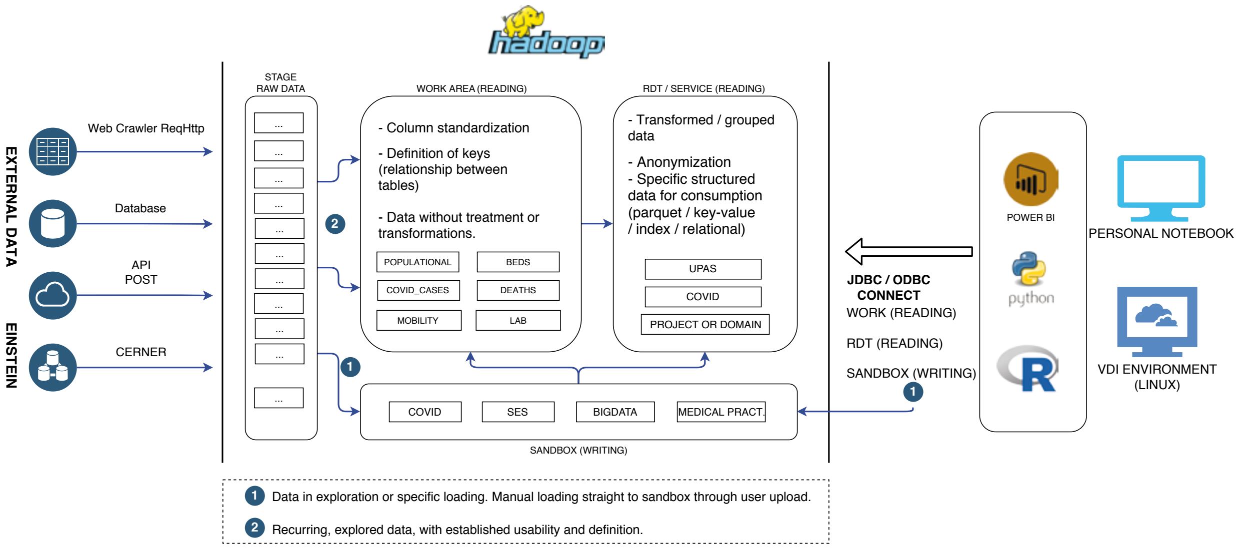
The work of identification, extraction, preparation and convergence of data can be arduous and time-consuming. On a team of scientists, it is possible that many members will need the same data, generating redundancy or even inconsistency in the results. To minimize this problem, it is common to create a data lake (sometimes called a data ocean, or variations thereof). In general, a data lake is a data repository in crude format, containing both structured and unstructured data. It is an environment that can perform tasks such as extracting, transforming and loading (ETL), large-scale data storage, and provision of this data in a uniform way.

To support the creation of analysis tools for the COVID-19 pandemic in Brazil, the team in the present study established a specific database (COVID Lake), a data lake with data of various scopes, as shown in Figure 3.

This structure served to support the activities of the different squads. Twenty-five databases were considered (public or for specific projects).

Many were conducted with various partners and include the following characteristics: behavior (questionnaires applied to the Brazilian population, aimed at understanding agglomerations and exposure to contamination); movement (data related to mobility using mobile phones); climate (weather stations and air pollution indices); demographic composition; and information from other countries.

Figure 3 – Architectural diagram of a data lake[15]



Source: Prepared by the authors.

Conclusion

Despite the complex experience of fighting the COVID-19 outbreak, it may serve as an accelerator in terms of contributions to the adoption of data science solutions – including the application of Artificial Intelligence. It is hoped that the results will be increasingly promising so that in the future, if a similar situation arises, there will be more mature analytical tools, capable of preventing harm that is currently not avoidable.

15 Structure based on Hadoop, HDFS and HBase, with Kerberos authentication, corporate Active Directory (AD). Access is restricted to the institution's internal network.

References

Akselrod-Ballin, A. et al. (2019). Predicting breast cancer by applying deep learning to linked health records and mammograms. *Radiology*, *292*(2), 331–342.

Alimadadi, A. et al. (2020). Artificial intelligence and machine learning to fight COVID-19. *Physiological Genomics*, *52*(4), 200–202.

Altmejd, A., Rocklöv, J., & Wallin, J. (2020). Nowcasting COVID-19 statistics reported withdelay: A case-study of Sweden. *arXiv.org*, q-bio.PE.

Barmparis, G. D., & Tsironis, G. P. (2020). Estimating the infection horizon of COVID-19 in eight countries with a data-driven approach. *Chaos, Solitons & Fractals*, *135*, 109842.

Barrozo, L. V. et al. (2020). GeoSES: A socioeconomic index for health and social research in Brazil. B. Lanza Queiroz, ed. *PloS one*, *15*(4), e0232074.

Batista, A. F. de M. et al. (2020). COVID-19 diagnosis prediction in emergency care patients: A machine learning approach. *medRxiv*, 1–8.

Brinati, D. et al. (2020). Detection of COVID-19 infection from routine blood exams with machine learning: A feasibility study. *Journal of Medical Systems*, *44*(8).

Britton, T. (2009). Stochastic epidemic models: A survey. *arXiv.org*, math.PR.

Chowell, G. et al. (2016). Mathematical models to characterize early epidemic growth: A review. *Physics of Life Reviews*, *18*, 66–97.

Collins, G. S. et al. (2015). Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): The TRIPOD Statement. 1–10.

Cosgriff, C. V. et al. (2019). Developing well-calibrated illness severity scores for decision support in the critically ill. *npj Digital Medicine*, 1–8.

DeCaprio, D. et al. (n.d.). Building a COVID-19 Vulnerability Index.*arXiv.org*.

Gao, L. et al. (2020). Prognostic value of NT-proBNP in patients with severe COVID-19. *Respiratory Research*, *21*(1), 83–7.

Hellewell, J. et al. (2020). Feasibility of controlling COVID-19 outbreaks by isolation of cases and contacts. *The Lancet. Global health*, *8*(4), e488–e496.

Hidalgo, E. S. (2019). Adapting the scrum framework for agile project management in science: Case study of a distributed research initiative. *Heliyon*, *5*(3), e01447.

Hirsch, J. S. et al. (2020). Acute kidney injury in patients hospitalized with COVID-19. *Kidney International*, *98*(1), 209–218.

Hornik, R. (2004). Some reflections on diffusion theory and the role of Everett Rogers. *Journal of Health Communication*, *9*(sup1), 143–148.

Jordan, R. E., Adab, P., & Cheng, K. K. (2020). COVID-19: Risk factors for severe disease and death. *British Medical Journal. Clinical Research Edition*, *368*, m1198.

Lai, S. et al. (2020). Effect of non-pharmaceutical interventions for containing the COVID-19 outbreak in China. *medRxiv*.

Lopez, L. R., & Rodo, X. (n.d.). A modified SEIR model to predict the COVID-19 outbreak in Spain and Italy: Simulating control scenarios and multi-scale epidemics. *medRxiv*.

MacIntyre, C. R., & Chughtai, A. A. (2020). A rapid systematic review of the efficacy of face masks and respirators against coronaviruses and other respiratory transmissible viruses for the community, healthcare workers and sick patients. *International Journal of Nursing Studies*, *108*, 103629.

Marston, C., Renedo, A., & Miles, S. (2020). Community participation is crucial in a pandemic. *Lancet*, *395*(10238), 1676–1678.

Martinez, E. Z., Aragon, D. C., & Nunes, A. A. (2020). Short-term forecasting of daily COVID-19 cases in Brazil by using the Holt's model. *Revista da Sociedade Brasileira de Medicina Tropical*, *53*(10223), 102433–35.

Meng, Z. et al.(n.d.). Development and utilization of an intelligent application for aiding COVID-19 diagnosis. *medRxiv*.

Nadim, S. S., Ghosh, I., & Chattopadhyay, J. (2020). Short-term predictions and prevention strategies for COVID-19: A model based study. *arXiv.org*, q-bio.PE.

Prem, K. et al. (2020). The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan, China: A modelling study. *The Lancet. Public health*, *5*(5), e261–e270.

Puca, M., & Buonanno, P. (n.d.). Using newspapers obituaries to nowcast daily mortality: Evidence from the Italian COVID-19 hot-spots. *medRxiv*.

Remuzzi, A., & Remuzzi, G. (2020). COVID-19 and Italy: What next? *Lancet*, *395*(10231), 1225–1228.

Roda, W. C. et al. (2020). Why is it difficult to accurately predict the COVID-19 epidemic? *Infectious Disease Modelling*, *5*, 271–281.

Santos, H. G. D. et al. (2020). Machine learning to predict 30-day quality-adjusted survival in critically ill patients with cancer. *Journal of Critical Care*, *55*, 73–78.

Schneble, M. et al. (2020). Nowcasting fatal COVID-19 infections on a regional level in Germany. *arXiv.org*, stat.AP.

Sun, Q. et al. (2020). Lower mortality of COVID-19 by early recognition and intervention: Experience from Jiangsu Province. *Annals of Intensive Care*, *10*(1), 33–34.

Swapnarekha, H. et al. (2020). Role of intelligent computing in COVID-19 prognosis: A state-of-the-art review. *Chaos, Solitons & Fractals*, *138*, 109947–48.

Wynants, L. et al. (2020). Prediction models for diagnosis and prognosis of COVID-19 infection: Systematic review and critical appraisal. *British Medical Journal. Clinical Research Edition*, *369*, m1328.

Uses of Artificial Intelligence in the context of COVID-10

Artificial Intelligence (AI) technologies are being employed in several ways to combat COVID-19. Figure 1 presents examples of AI applications in different phases of the crisis and for different purposes, such as the production of personalized information, the monitoring of infections in real time, or even the transportation and delivery of materials.

Figure 1 – Examples of AI applications at different stages of the COVID-19 crisis

Accelerating research
Open data projects and distributed computing to find AI-driven solutions to the pandemic, e.g. *drug and vaccine development*

Detection	**Early warning** Detecting anomalies and digital "smoke signals:, e.g. *BlueDot*	**Diagnosis** Pattern recognition using medical imagery and symptom data, e.g. *CT sans*	
Prevention	**Prediction** Calculating a person's probability of infection, e.g. *EpiRisk*	**Surveillance** To monitor and track contagion in real time, e.g. *contact tracing*	**Information** Personalised news and content moderation to fight misinformation, e.g. *via social networks*
Response	**Delivery** Drones for materials' transport; robots for high-exposure tasks at hospitals, e.g. *CRUZR robot*	**Service automation** Deploying triaging virtual assistants and chatbots, e.g. *Canada's COVID-19 chatbot*	
Recovery	**Monitor** Track economic recovery through satellite, GPS and social media data, e.g. *WeBank*		

Source: OECD, *Using artificial intelligence to help combat COVID-19* (2020).

Public health and surveillance: AI for contact tracing

Contact tracing is a public surveillance strategy that has been implemented as a prevention mechanism in the health sector. It refers to the process used to identify, inform, and monitor individuals who came into close contact with someone infected by the virus. This process depends increasingly on the use of technologies, especially AI.

In the context of COVID-19, AI has been used in strategies that aim to decrease viral transmission, namely: infrared fever screening of public spaces; AI-based drones and robots to detect movement, social meetings, and unmasked individuals; and the use of AI-guided contact tracing algorithms to send personalized text messages to citizens.

In China, one example of AI-based contact tracing is supported by plug-ins installed in apps broadly used by the population. The plug-in collects data from users and feeds a central database, whose information is analyzed via AI tools. Next, the algorithm emits color codes to users to indicate whether or not they are restricted in their comings and goings, in addition to warning recent close contacts in case of a positive COVID-19 diagnosis.

Article II

Facing this unprecedented crisis, the most immediate response of most governments has been the application of strict social distancing rules coupled with partial to total lockdowns.

Digital Contact Tracing to Fight against COVID-19

By Sacha Alanoca[16], Nicolas Guetta Jeanrenaud[17], Nyasha Weinberg[18], R. Buse Çetin[19] and Nicolas Miailhe[20]

An unprecedented public health crisis

Since the outbreak of COVID-19 in Wuhan, China in late 2019 and its classification as a pandemic by the World Health Organization (WHO) in March 2020, the number of deaths and infections has continued to rise globally. As of July 10, 2020, the count was at over 12.3 million diagnosed cases and over 555,000 deaths. In Latin America, numbers have recently spiked, reaching over 3.3 million infections and 143,000 deaths, with the highest concentration of cases in Brazil, Peru and Chile[21]. Facing this unprecedented crisis, the most immediate response of most governments has been the application of strict social distancing rules coupled with partial to total lockdowns.

These measures slow down the rate of infections, or “flatten the curve”—in reference to the flat shape of charts that show a reduced trend in daily cases enabling healthcare systems to treat the flow of incoming patients. However, without capacity for large-scale testing, on the one hand, and prospects for treatment and vaccine to be deployed in the near future, on the other, these efforts can only delay the spread of the pandemic, not stop it.

16 Senior AI Policy Researcher and Head of Community Development at The Future Society. She holds a Master’s degree from Science Po Paris where she specialized in Emerging Economies and Digital Innovation.

17 Graduate student in Technology & Policy at MIT, where he specializes in computational social sciences and information systems. He also holds a Master’s degree in Civil Engineering from l’Ecole des Mines de Paris.

18 Future Society affiliated Research Fellow, currently on a reconstitution fellowship. She is a legal and public policy expert, a member of the UK bar with an MPP from Harvard Kennedy School.

19 AI Policy Researcher at The Future Society. She holds a Master’s degree in International Public Management from Sciences Po Paris School of International Affairs (PSIA) where she specialized in economic policy and global governance. She has a Bachelor’s degree in Social Sciences & Middle Eastern Studies from Sciences Po Paris.

20 Co-founder of The Future Society. He is also a Steering Committee member of the AI Commons partnership, a member of the AI Group of experts at OECD, and of the Global Council on Extended Intelligence (CXI), among other organizations. He teaches at the Paris School of International Affairs (Sciences Po), at the IE School of Global and Public Affairs in Madrid, and at the Mohammed bin Rashid School of Government in Dubai. He is also a Senior Research Associate at Harvard, and a Fellow at IE Business School in Madrid.

21 The WHO regularly updates a global COVID-19 Disease Dashboard. Available at: https://COVID19.who.int

Moreover, these measures have very significant socioeconomic costs. Since the pandemic outbreak, it is estimated that over 13 million people have registered for unemployment in France[22] and over 33 million in the United States[23]. Millions are unemployed across Latin America. In Brazil, a record 7.8 million people lost their jobs between March and May 2020, leaving the percentage of the population that are working below 50% . It is also necessary to take into account the considerable impacts of the current scenario on the mental health of the population, with rising levels of stress and anxiety, as well as the yet unknown costs of suspensions or delays of routine healthcare treatment (Ornell et al., 2020).

Contact tracing as a quick and accurate mitigation technique

Confronted with the urgent need to mitigate the crisis, governments around the world have explored a combination of medical and technological tools. Among these, contact tracing describes a variety of techniques used to identify people who may have come into contact with an individual who received a positive diagnosis for COVID-19, taking appropriate action to inform, isolate, and treat them.

In the past, manual contact tracing has systematically been deployed to mitigate epidemics such as tuberculosis, measles, HIV and, more recently, to limit the spread of Ebola and SARS (Hart et al., 2020). Relative to other diseases, however, COVID-19 is considered to be highly contagious[25]. Labor-intensive manual contact tracing, which relies on human memory and trained medical staff, lacks both the speed and accuracy necessary to match the spread of the virus.

Through the mobilization of digital planning and analytical tools, digital contact tracing can improve this scenario. Smartphones and smart bracelets automate this process, enabling proximity tracking, digital health monitoring, or even patient identification. When coupled with other appropriate measures, such as social distancing and testing, digital contact tracing can help to break contamination chains and prevent new cases by alerting exposed populations to risk. Several countries that have effectively "flattened the curve" of the first COVID-19 outbreak wave, such as Taiwan, South Korea, Singapore, and China, have successfully deployed this strategy. According to the MIT Technology Review[26], there are currently 47 contact tracing applications deployed across over 30 nations.

(...) contact tracing describes a variety of techniques used to identify people who may have come into contact with an individual who received a positive diagnosis for COVID-19, taking appropriate action to inform, isolate,
and treat them.

[22] More information at: https://www.rtl.fr/actu/conso/coronavirus-pourquoi-y-a-il-autant-de-salaries-en-chomage-partiel-en-france-7800466953

[23] More information at: https://www.bbc.com/news/business-52570600

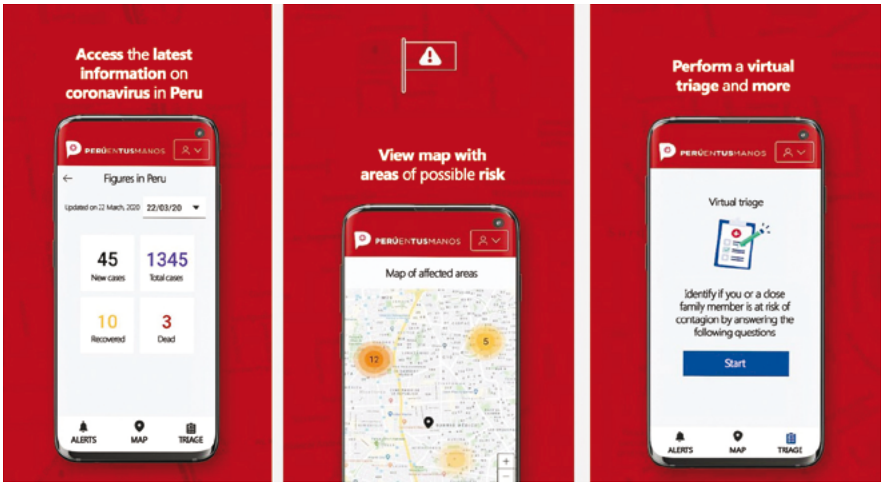
[24] More information at: https://edition.cnn.com/2020/07/01/americas/latin-america-coronavirus-unemployment-intl/index.html

[25] The median incubation period is five days, with 97.5% of those who develop symptoms doing so within 11.5 days (Lauer et al., 2020; Li et al., 2020). Estimates of the asymptomatic share of infected individuals range from 15.5% (Mizumoto et al., 2020) to 56% (Arons et al., 2020).

[26] More information at: https://www.technologyreview.com/2020/05/07/1000961/launching-mittr-Covid-tracing-tracker

Issues that have been raised include its performance and impact on data privacy, human rights, stigmatization of individuals, mistrust of public authorities and, finally, fear of establishing mass surveillance.

Figure 1 – The "PerúEnTusManos" application, deployed by the Peruvian Government



Source: "PerúEnTusManos", Presidencia del Consejo de Ministros (Peru).

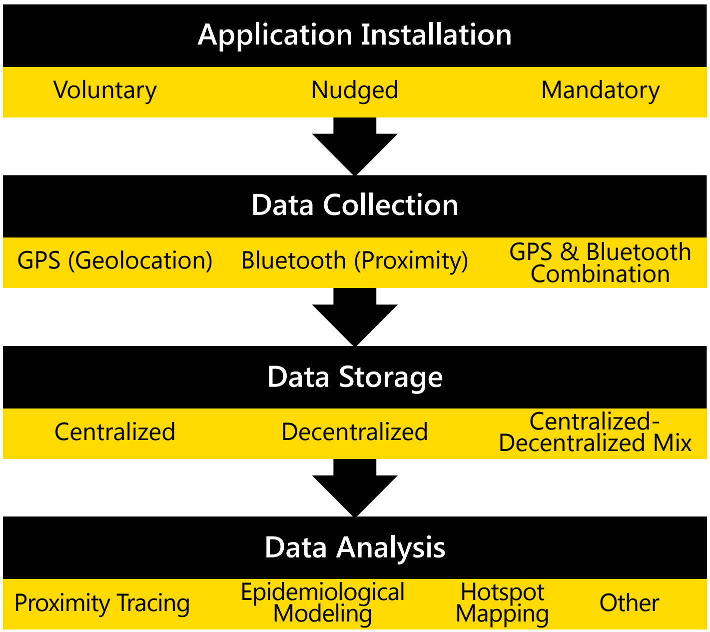
However, worldwide concerns have quickly arisen about the widespread and generalized adoption of digital contact tracing. Issues that have been raised include its performance and impact on data privacy, human rights, stigmatization of individuals, mistrust of public authorities and, finally, fear of establishing mass surveillance. Disinformation and lack of clear ethical, legal and technical safeguards have polarized the public debate in several countries at a time when, more than ever, it is necessary to build trust and prevent civil liberties from being sacrificed in the name of public health.

There is a pressing need to co-design governance mechanisms that maximize the health benefits of contact tracing applications while mitigating their potential adverse effects. The urgency of the health situation should not impact our collective ability to make the right decision, and to responsibly navigate potential tensions between public health, safety and civil liberties. Evidence suggests that the widespread adoption of these applications is reliant on public trust, further reinforcing the need for an ethical framework that governs their development.

Technical alternatives and trade-offs

Contact tracing applications are based on a range of technologies and privacy-preserving protocols. They can be voluntary (available from mobile application stores), mandatory, or nudged. The data collection process is based on proximity (usually via Bluetooth), relies on GPS localization data, or is mixed. Data can be stored locally on individuals' mobile devices in a decentralized approach, on a centralized server, or with a mixed approach. Finally, the analysis that is conducted by the relevant authorities varies, ranging from simple proximity calculation to epidemiological modeling, hotspot mapping, and more.

Figure 2 – Digital contact tracing technical features



Source: The Future Society.

Application installation

One technical imperative for the success of a contact tracing application is widespread installation and adoption by individuals. While there is still no consensus among epidemiologists on the transmission rate of COVID-19, a study conducted at the University of Oxford estimated that, with a minimum adoption rate of 60%, such applications could effectively stop the epidemic[27]. This is, however, a minimum threshold - the authors of the report subsequently pointed out that lower levels of adoption would already be vital to curb the spread of the virus[28].

Although the installation of these applications is of great importance for governments' fight against COVID-19, authorities in several countries have taken a radical approach, making it mandatory for all citizens. In China, a "contact detector" plugs into the existing and widely used applications WeChat and Alipay. The program analyzes health and travel data to assign "risk colors" to individuals, potentially denying them access to stores and essential services[29]. In Kuwait and Bahrain, the application is separate from existing phone functionalities, but its installation is required by law.

The vast majority of countries have settled on voluntary applications, although personalized or generic incentives, or "nudges," can be embedded in their functionalities. Some offer additional information on where to get tested for COVID-19 (Australia) or hospital availability (Turkey), while others release

One technical imperative for the success of a contact tracing application is widespread installation and adoption by individuals.

[27] Avaliable at: https://www.research.ox.ac.uk/Article/2020-04-16-digital-contact-tracing-can-slow-or-even-stop-coronavirus-transmission-and-ease-us-out-of-lockdown

[28] More information at: https://www.technologyreview.com/2020/06/05/1002775/Covid-apps-effective-at-less-than-60-percent-download

[29] More information at: https://www.nytimes.com/2020/05/26/technology/china-coronavirus-surveillance.html

news updates connected to the pandemic (Bulgaria) or health tips (Qatar). The extent to which these additional incentives will lead to compulsory adoption of the application will depend on whether there are alternative routes to access identical services.

Data Collection

According to information from the COVID-19 Digital Rights Tracker, by the British company Top10VPN, with regard to the data collection process, 34% of existing contact tracing applications use GPS, 35% use Bluetooth, and 24% use a combination of both. This distribution highlights the lack of consensus around the most effective technology for this task.

Bluetooth protocols rely solely on proximity detection. A mobile device records other Bluetooth signals within a given range for a given time, in a so-called “digital handshake.” During the exchange, each device collects pseudonymized tokens[30]—typically chains of numbers that change randomly several times a day—as identifiers of the other users. A notification mechanism informs individuals when they are close to a user signaled as infected.

Countries such as Mexico, Italy, Japan and the UK have all adopted peer-to-peer Bluetooth Low Energy (BLE) protocols, while Singapore uses the Bluetooth-based BlueTrace protocol. In most cases, proximity is measured within 1 meter, and pseudonymized tokens are exchanged after 15 minutes, as shown in Figure 3 by the French example.

GPS schemes, on the other hand, rely on mobile data to reconstruct users' location histories. When individuals are flagged as infected, the application retraces every other user with whom they have crossed paths. The GPS protocol has the additional feature of highlighting geographic hotspots of the virus, enabling targeted measures, which is not possible using Bluetooth. However,

Figure 3 – The Stopcovid Proximity-Tracing application, deployed by the French Government

Source: French Government (2020).

[30] Physical devices that generate a temporary protection password for the accounts used by the user, assisting their personal safety.

this technique is less accurate at recording proximity, especially indoors or during underground travel. In terms of privacy, GPS protocols have been associated with some of the most intrusive applications, such as BeAware in Bahrain, Shlonik in Kuwait, and Smittestopp in Norway[31].

Finally, some application protocols combine Bluetooth and GPS data for contact tracing. An example of this is the MIT-based Private Kit SafePaths platform, which uses both types of data to record individuals' locations. Free and open-source, the protocol has been adopted in several countries, such as Cyprus[32].

Given the sensitive nature of the data at hand, data storage architecture has been the subject of much debate among application developers and privacy experts.

Data storage

In addition to contact tracing applications, many other technologies request additional personal user information. Ketju in Finland, and Hayat Eve Sığar in Turkey, require valid phone numbers for authentication, while in Iceland (only for individuals who have been diagnosed with COVID-19), Qatar, and Kuwait, authentication is done using National ID numbers. Some applications, such as ViruSafe in Bulgaria, collect users' age and medical history at registration. All contact tracing applications also collect COVID-19 diagnosis data to notify at-risk individuals.

Given the sensitive nature of the data at hand, data storage architecture has been the subject of much debate among application developers and privacy experts. In centralized solutions, data collected by contact tracing applications are directly recorded in a main server, which is usually highly secure and easily accessible for government agencies. Decentralized solutions, on the other hand, keep logs of proximity and location on users' devices, which are stored locally[33].

Regardless of which storage protocol is selected, most contact tracing applications mitigate privacy concerns by using data de-identification. Although complete data anonymization is never achievable in practice (Rocher, Hendrickx & Montjoye, 2019), different methods of data pseudonymization are integral aspects of most contact tracing applications. Applications such as Stopp Corona in Austria, StopCovid in France, and TraceTogether in Singapore assign unique IDs to users, which in some cases change over time for additional security. Both the MIT Private Kit SafePath and the Google-Apple protocols use differential privacy to ensure that aggregate data made available by the application does not enable individual users to be reidentified.

Data analysis

The data collected by contact tracing applications can serve different goals of government agencies. The minimal use of contact tracing data consists of flagging proximity between infected individuals and application users (as

[31] More information at: https://www.amnesty.org/en/latest/news/2020/06/bahrain-kuwait-norway-contact-tracing-apps-danger-for-privacy

[32] More information at: https://www.financialmirror.com/2020/04/06/technology-recruited-in-fight-against-coronavirus

[33] As examples of these approaches, the decentralized solution known as DP3T, developed by Google and Apple, is featured in applications in Finland, Malaysia, and Switzerland. France and Germany have also adopted what they call a "centralized-decentralized contact-tracing protocol." The ROBERT (ROBust and privacy-presERving proximity Tracing) protocol stores data initially on devices, but sends data to a centralized server once users have tested positive.

> The minimal use of contact tracing data consists of flagging proximity between infected individuals and application users (as measured by Bluetooth or GPS). However, several countries leverage data from contact tracing applications for different purposes.

measured by Bluetooth or GPS). However, several countries leverage data from contact tracing applications for different purposes. The UK's initial plan for digital contract tracing, for example, allowed data collected from the NHS COVID-19 application to also feed epidemiological models to study virus spread[34].

Ethical risks raised by digital contact tracing

The adoption of digital contact tracing applications raises a number of relevant ethical questions. Given the extent and sensitive nature of the collected data, these technologies have the potential to undermine fundamental civil liberties and human values such as privacy, data protection, human autonomy and fairness.

Privacy and data protection

All digital contact tracing requires some degree of access to information that could potentially infringe on privacy, such as health status, location, and credit card information. Thus, privacy risks are inherent in the use of this technology. For instance, other apps installed in a smartphone may listen in on the digital contact tracing app and send data to third parties, and anonymized data is susceptible to re-identification. According to the COVID-19 Digital Rights Tracker, 20% of digital contact tracing apps do not have privacy policies. Therefore, lack of information and legal, technical, and political safeguards raise major concerns.

In this context, there are two important aspects: the actual privacy-preserving characteristics of the apps themselves; and the extent to which they offer users control of privacy. Actual privacy implies limiting information exposure to the greatest extent possible, while control of that privacy means allowing individuals to make transparent choices about the use of their data (Loi et al., 2020). Fighting against COVID-19 through digital contact tracing may imply temporary adjustments in terms of actual privacy; however, individuals should always be empowered to make these choices themselves.

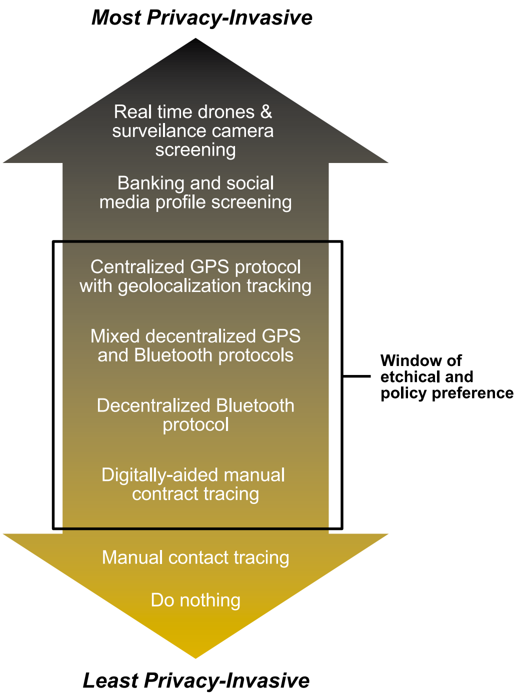
One important aspect is that data pseudonymization and the technical steps taken in this direction by contact tracing applications may not fully mitigate the risk. Claims have been made that several applications, including France's StopCovid, have not sufficiently preserved anonymity, despite user encryption. In 2013, researchers studied location data from 1.5 million people and found that it was so specific to individual habits that 95% of them could be identified (Rocher, Hendrickx & Montjoye, 2019). When contact tracing applications combine location data with other sensitive information, as in Taiwan and South Korea, there is a higher risk of privacy breaches and even mass surveillance.

There are concerns about the establishment of surveillance infrastructures by governments and large technology companies through digital contact tracing. Caught between economic collapse and social disaster, some governments have deployed digital contact tracing tools at speed and without going through democratic and informed consent procedures. There is fear that ex-

[34] More information at: https://social.techcrunch.com/2020/05/05/nhs-COVID-19-the-uks-coronavirus-contacts-tracing-app-explained

ceptional measures infringing on civil liberties will remain after the pandemic and become “the new normal.” Ensuring that digital contact tracing is voluntary and temporary is crucial, in order to avoid expanding the reach of surveillance beyond its initial purposes.

Figure 4 – Privacy spectrum of applications to fight against COVID-19



Source: The Future Society.

Stigma and discrimination

Concerns have been raised about the impact of contact tracing applications on social groups that have historically experienced discrimination, stigma, and abuse. There are three significant risks, particularly in states that impose criminal sanctions on COVID-19 transmission, or use the data collected from applications to make decisions on “passporting” to certain services. The first risk is that the data will be used to stigmatize particular groups, such as women (Davis, 2020). The second is that insights from location data may be used to stigmatize and blame specific minority groups[35]. The third risk is that groups will avoid using contact tracing applications, prohibiting access to services or places.

(...) data pseudonymization and the technical steps taken in this direction by contact tracing applications may not fully mitigate the risk.

35 More information at: https://news.un.org/en/story/2020/03/1060602

Without specific measures aimed at bridging the digital divide, the user base will not reflect the entire population, and specific subgroups will be deprived of the applications' services.

The risk of stigmatization is intrinsic to digital contact tracking because it entails collecting data on entire populations. Used outside the purpose of monitoring COVID-19 exposure, the data can lead to singling out virus "hot zones." Ethnic minority neighborhoods could become an easy target for stigmatization and discrimination, as well as front-line and second-line workers such as food delivery riders, cashiers and drivers. When these professions are carried out by marginalized groups, the impact of digital contact tracing is even more severe. Stigmatization creates alienation and harms social cohesion.

Accessibility

Contact tracing applications also rely on technological access and digital literacy for mass adoption. Without specific measures aimed at bridging the digital divide, the user base will not reflect the entire population, and specific subgroups will be deprived of the applications' services. Although increasingly widespread, access to mobile technology remains incomplete around the world: According to the Pew Research Center, in 2019, two-thirds of the world's population did not own a smartphone.

Digital literacy is often highly correlated with other socioeconomic characteristics. A recent review of Twitter users in Italy found them to be on average younger and more highly educated than the overall population (Vaccari et al., 2013). It should also be noted that people with disabilities have been historically disenfranchised by the Internet and digital platforms[36].

According to Floridi (2020), these applications will work better when they are more widespread. However, this will be the case where levels of digital literacy and ownership of mobile phones are higher. Therefore, there is a very concrete risk of privileging the already privileged, as well as their residential areas. In this context, the digital divide may become a biological divide.

The case for an ethical framework for digital contact tracing

It is our collective responsibility to develop and adopt an ethical framework to navigate conflicts between public health, safety, economic activity, and civil liberties. The urgency of the situation caused by COVID-19 should not impact our capacity to build a comprehensive

[36] More information at: https://www.pewresearch.org/global/2019/02/05/smartphone-ownership-is-growing-rapidly-around-the-world-but-not-always-equally

framework to guide the choices of citizens, app developers and policymakers. Informed individuals are more willing to accept potentially significant but necessary sacrifices when choices are voluntary and ethically justified. Thus, building a trustworthy ethical framework is key to ensuring social cohesion and the effectiveness of contact tracing applications.

Chart of Ethical Principles	
Purpose and performance	The purpose of the applications should be clear, understandable within the broader context, measurable, and independently auditable.
Voluntariness and reversibility	Individuals must be able to choose whether to install apps of their own free will, with no negative consequences if they choose not to do so. Users should be able to deactivate apps temporarily or permanently at any time, with no remaining personal data or proximity information being stored by app developers or third parties.
Privacy by design	Contact tracing apps should achieve the strongest levels of privacy protection. Data storage should be secure and pseudonymized.
Minimal use of data and technology	Data collection must be proportionate, justified, and have a defined expiration date. Only the minimal data necessary to fulfill the purpose of the applications should be used and stored.
Transparency and verifiability	The complete source code for apps and core tracing protocols must be freely available and reproducible, without access restrictions for audits.
Non-discrimination and non-stigmatization	App developers and policymakers should ensure that contact tracing applications do not stigmatize or discriminate against people who have tested positive for COVID-19 or their relatives, categories of social workers, neighborhoods, or people who do not wish to use the applications.
Accessibility	It should be recognized that smartphone applications and Internet connectivity are not accessible to the entire population. Some citizens may not have smartphones, and persons with disabilities, the elderly, or less tech-savvy people might not be able to use such applications. Complementary and alternative solutions should be developed to ensure accessibility.
Notice and informed consent	Information on the purposes and features, and data collection, should be clearly presented to users. Informed and explicit consent should be a prerequisite for applications. Design-dark patterns (e.g., nudges via push notifications, apps downloaded on smartphones by default, and hidden features to deactivate or remove apps) should be avoided.
Accountability	Contact tracing apps must be continuously evaluated and audited by legitimate independent entities in which the public can place their full trust. All stakeholders involved in the design and deployment of apps should be accountable according to clear legal frameworks for penalties and responsibilities.

In recent years, public trust in political institutions and tech companies has been eroding, making it all the more relevant and necessary to proactively seek public awareness and consent before deploying contact tracing applications.

Conclusions

As the number of COVID-19 positive cases continues to rise globally, it is our collective responsibility not only to explore all medical and technological solutions, but also to manage them responsibly. In recent years, public trust in political institutions and tech companies has been eroding, making it all the more relevant and necessary to proactively seek public awareness and consent before deploying contact tracing applications. An ethical framework can help to build a common understanding and guide the choices of different stakeholders. For this framework to be actionable, principles will have to be translated into specific criteria and coupled with audit parameters developed and implemented by third parties, in order to cultivate trust among users and other stakeholders.

References

Arons, M. M. et al. (2020). Presymptomatic SARS-CoV-2 infections and transmission in a skilled nursing facility. *New England Journal of Medicine*, *382*, 2081.

Davis, S. (2020, 29 Abril). *Contact tracing apps: Extra risks for women and marginalized groups*. Health and Human Rights Journal. Recuperado de https://www.hhrjournal.org/2020/04/contact-tracing-apps-extra-risks-for-women-and-marginalized-groups.

Floridi, L. (2020, 18 Abril). *Mind the app: Considerations on the ethical risks of COVID-19 apps.* Onlife. Recuperado de https://thephilosophyofinformation.blogspot.com/2020/04/mind-app-considerations-on-ethical.html.

Governo da França. (2020). *ProjetStopCovid: Dossier de presse (21 mai 2020).* Recuperado de https://decryptageo.fr/wp-content/uploads/2020/05/Dossier-de-presse-Pojet-StopCovid.pdf.

Hart, V. et al. (2020). Outpacing the virus: Digital response to containing the spread of COVID-19 while mitigating privacy risks. *Edmond J. Safra Center for Ethics.* Recuperado de https://ethics.harvard.edu/outpacing-virus.

Lauer, S. A. et al. (2020). The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: Estimation and application. *Annals of Internal Medicine*, *172*, 577.

Li, Q. et al. (2020). Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia. *New England Journal of Medicine*, *382*, 1199.

Loi, M. et al. (2020). *Ethical framework for human-centric public health digital surveillance*. Recuperado de https://docs.google.com/document/d/19F_hXIlPvDKCk8JTfxNXOuex0r_GpmPEUuoSUMEj-zY/edit.

Mizumoto, K. et al. (2020).Estimating the asymptomatic proportion of coronavirus disease 2019 (COVID-19) cases on board the Diamond Princess cruise ship, Yokohama, Japan, 2020. *Eurosurveillance*, *25*, 2000180.

Ornell, F., Schuch, J. B., Sordi, A. O., & Kessler, F. H. P. (2020). "Pandemic fear" and COVID-19: mental health burden and strategies. *Brazilian Journal of Psychiatry*, *42*(3), 232-235.

Rocher, L., Hendrickx, J. M., & Montjoye, Y. (2019). Estimating the success of re-identifications in incomplete datasets using generative models. *Nature Communications*, *10*, 3069.

Vaccari, C. et al. (2013). Social media and political communication: A survey of Twitter users during the 2013 italian general election. *Rivista Italiana di Scienza Politica.*

Interview I

Dr. Eneida A. Mendonça

Professor of Pediatrics and Biostatistics at Indiana University, vice president of Research Development and interim director at the Clem McDonald Center for Biomedical Informatics at the Regenstrief Institute.

I.S.O._ There has been increasing discussion of the possible contributions of Artificial Intelligence (AI) to the field of health. What are the challenges being faced for its implementation in the sector?

E.M._ The use of algorithms and AI tools to assist physicians, nurses and other professionals in their practices has been constantly growing. These solutions have the potential to enhance efficiency, effectiveness and fairness of access in the field of health. However, although the outlook is optimistic, it is important to consider the challenges involved in the task.

The discrepancy between efforts to develop AI models and solutions, on the one hand, and their successful use, on the other, reflects the difficulties of implementing decision support tools in general. Even though technical obstacles exist, most of the challenges involve: the complexity of tailoring applications to integrate them into systems such as electronic health records; lack of alignment in relation to the real needs of users; lack of expectation management; and ethical and legal aspects. All these factors need to be added to the equation to achieve genuine benefits.

AI offers many opportunities for solutions that assist in the diagnosis of clinical problems, disease therapy, and cost reduction, generating a significantly positive impact on the area of health as a whole. However, it is necessary to be aware of the current capacity and limitations of these techniques in order to avoid frustration and a consequent antagonistic movement that would hinder the progress of AI in the sector. The ideal is a realistic balance between what can be done and what is adequate. Informing and educating all audiences involved – informatics workers, engineers, managers, health professionals and the general population – in relation to the principles and use of these tools is fundamental.

I.S.O._ In the context of the data ecosystem in the health sector, where there is major heterogeneity of sources and large volumes of data are available, how should AI governance be handled?

E.M._ The engagement of the scientific community, health professionals and citizens is essential for equitable and transparent data integration and use. AI governance for clinical practices should include, not only technology developers, but also representatives of service providers, managers, users and patients. It should consider analysis of the application's performance and its

> "Machine learning methods tend to perform well in terms of extracting characteristics, patterns and rules from complex and large amounts of data (big data), but do not produce meaning, purpose, sense of justice or equity. It is essential to recognize that algorithms 'learn' based only on the data that"

cost-benefit potential to improve health and lower healthcare costs.
To be successful in the area of health, AI algorithms must be trained with data that is representative of the characteristics of the real population – only then will the generated models achieve adequately accurate results. In view of the increased quantity and diversity of data related to the sector (electronic medical records, genetic data, and social determinants of health, for example), an ecosystem must be created that enables the storage, integration and analysis of this data.
Various options for data structures and standards for representation of biomedical information are already available, such as CID, LOINC and SNOMED codes. However, their usage is not universal, substantially reducing the capacity for AI use. The adoption of common data models – for example, Observational Medical Outcomes Partnership (OMOP) and Informatics for Integrating Biology and the Bedside (i2b2) – as well as standards such as HL7 FHIR, which enable standardized data transfer, must be prioritized, along with continuity in discussions of policies for data sharing, governance, mechanisms for assessing systems, and algorithms.

I.S.O._ Since AI solutions are based on data, what are the risks involved in implementing them in health? How can these risks be circumvented?

E.M._ Apart from the complexity of the data used to train models, the cycle for development, validation and implementation of AI tools requires adopting very controlled and rigorous models from the technical-scientific point of view. In practice, in terms of patient risk, these algorithms are similar to medications and medical equipment.
The models and tools should also be assessed in relation to performance, utility, vulnerabilities and biases. Variations in local care and therapy standards, populations with different characteristics, and biases in the selection of learning and validation data are examples of factors that can significantly affect the use of algorithms and bring about undesirable consequences.
Machine learning methods tend to perform well in terms of extracting characteristics, patterns and rules from complex and large amounts of data (big data), but do not produce meaning, purpose, sense of justice or equity. It is essential to recognize that algorithms "learn" based only on the data that trains them. If the data set contains biases, the algorithm will have the potential to amplify them. It is also important to have transparency regarding how the data will be used and how the models will be validated. In addition to reproducibility in different populations, the balance between innovation, safety and privacy of the data of individuals needs to be respected.
Finally, I suggest reading a recent publication from the National Academy of Medicine[37] on adequate implementation of AI applications in the health sector. The authors of the document present detailed recommendations and offer interesting reflections for the community.

[37] Available at: https://nam.edu/artificial-intelligence-special-publication.

Interview II

I.S.O._ Are there any existing frameworks proposed by WHO for regulating, comparing and certifying AI-based methods in the field of digital health? If so, how are these processes implemented in practice?

B.M.J._ In the fight against COVID-19, technologies like AI are used to assist with population screening, track infection cases, monitor resources - and more notably - to define the social determinants of health, which are the fundamental equity and human rights element in the fight against COVID-19. However, while AI and technologies like it hold huge potential for good, we must also leave space to discuss the real-life ethical questions surrounding their use. We must ensure that AI is used correctly in healthcare systems – particularly as regards equitable access and patient privacy.

WHO is developing the Global Digital Health Strategy. It proposes a framework for regulating, benchmarking, and certifying artificial intelligence and digital health medical devices for implementation by Member States. Jointly with the International Telecommunication Union (ITU), WHO is working on developing benchmarking guidance on AI for health programs. WHO has established expert groups on the ethics of AI and regulation of AI to develop the framework.

The framework on AI for health will include the following areas of focus:

- Ensuring equitable access to AI;
- Determining the interplay of AI and the digital divide;
- Preserving individual rights to autonomy, privacy, informed consent and freedom from bias and discrimination;
- Ensuring the provision of education about how AI functions and makes decisions;
- Ensuring equal access to databases regardless of financial means;
- Maintaining human control of AI; and
- Strengthening public oversight and regulation of the private sector.

Also, WHO and ITU established a Focus Group on Artificial Intelligence for Health (FG-AI4H) in July 2018. FG-AI4H is developing a benchmarking process for health AI models that can act as an international, independent, standard evaluation framework.

I.S.O._ Are there specific AI initiatives that WHO has implemented or is monitoring in the context of the COVID-19 pandemic?

Mr. Bernardo Mariano Junior

CIO and Director of the Department of Digital Health and Innovation, World Health Organization (WHO).

> "At the heart of the initiative is creating a community of practice for public health intelligence (PHI) that includes Member States, international organizations, research institutes and other partners and collaborators. Its ultimate objective is saving lives".

B.M.J._ In September 2017, WHO accepted leadership of the Epidemic Intelligence from Open Sources (EIOS) initiative – a unique collaboration among various public health stakeholders around the globe. It brings together new and existing initiatives, networks and systems to create a unified all-hazards, One Health approach to early detection, verification, assessment and communication of public health threats using publicly available information. At the heart of the initiative is creating a community of practice for public health intelligence (PHI) that includes Member States, international organizations, research institutes and other partners and collaborators. Its ultimate objective is saving lives through early detection of threats and subsequent intervention.

The EIOS community of practice is supported by an evolving EIOS system for public health intelligence that not only connects other systems and actors – including ProMed, HealthMap and the Global Public Health Intelligence Network (GPHIN) – but also promotes and catalyzes new and innovative collaborative development using artificial and augmented intelligence, primarily in the domain of computational linguistics and natural language processing. The EIOS system builds on a long-standing collaboration between WHO and the Joint Research Centre (JRC) of the European Commission (EC) to develop a system and respond to the need for a global initiative to bring together PHI efforts.

Since the start of the outbreak, members of the EIOS community have been working on developing advanced AI and machine learning features to help manage the unprecedented volume of information from both official and unofficial sources. This involves looking at improved ways to filter, contextualize and visualize all of the content coming in, such as the introduction of the additional content from social networks (Twitter), as well as news article reliability recognition by analyzing the tone and writing style.

Domain Report

The dynamics of registration of domains in Brazil and around the world

The Regional Center for Studies on the Development of the Information Society (Cetic.br) carries out monthly monitoring of the number of domain names in country code top-level domains (ccTLD) registered among G20 countries[38]. Combined, they exceed 79.50 million registrations. In August 2020, domains registered under .de (Germany) reached 16.53 million, followed by China (.cn), the United Kingdom (.uk) and Russia (.ru), with 16.05 million, 9.50 million and 4.96 million registrations, respectively. Brazil had 4.41 million registrations under .br, occupying 5th place on the list, as shown in Table 1[39].

Table 1 – Registration of domain names among G20 countries – August 2020

Position	G20 countries	Number of domains	Source
1	Germany (.de)	16.531.825	www.denic.de
2	China (.cn)	16.048.918	research.domaintools.com/statistics/tld-counts/
3	United Kingdom (.uk)	9.501.094	www.nominet.uk/news/reports-statistics/uk-register-statistics-2020/
4	Rússia (.ru)	4.960.220	cctld.ru
5	**Brazil (.br)**	**4.408.632**	**registro.br/dominio/estatisticas/**
6	France (.fr)	3.566.512	www.afnic.fr/en/resources/statistics/detailed-data-on-domain-names/
7	European Union (.eu)	3.531.400	research.domaintools.com/statistics/tld-counts/
8	Italy (.it)	3.315.268	nic.it
9	Australia (.au)	3.205.126	www.auda.org.au/
10	Canada (.ca)	2.935.244	www.cira.ca
11	India (.in)	2.200.000	www.registry.in/
12	United States (.us)	1.685.195	research.domaintools.com/statistics/tld-counts/
13	Japan (.jp)	1.596.328	jprs.co.jp/en/stat/
14	South Africa (.za)	1.264.123	www.zadna.org.za
15	South Korea (.kr)	1.107.229	krnic.or.kr/jsp/eng/domain/kr/statistics.jsp
16	Mexico (.mx)	910.012	research.domaintools.com/statistics/tld-counts/
17	Argentina (.ar)	612.656	nic.ar/es/dominios/estadisticas
18	Indonesia (.id)	434.525	pandi.id/?lang=en
19	Turkey (.tr)	430.555	www.nic.tr/index.php?USRACTN=STATISTICS
20	Saudi Arabia (.sa)	69.293	www.nic.sa/en/view/statistics

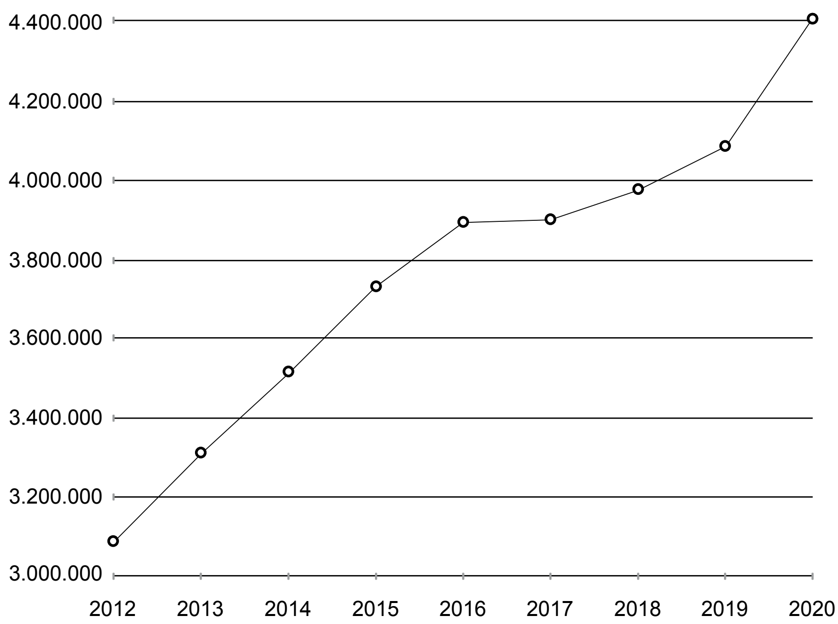
Data collection date: 08/31/2020

[38] Group of the 19 largest economies in the world and the European Union. More information available at: https://g20.org/en/Pages/home.aspx

[39] The table presents the number of ccTLD domains, according to the sources indicated. The figures correspond to the record published by each G20 country. For countries that do not present or publish official statistics provided by the authority for registration of domain names, the figures were obtained from: https://research.domaintools.com/statistics/tld-counts. It is important to note that there are variations among the reference periods, although it is always the most up-to-date one for each country. The comparative analysis for domain name performance should also consider the different management models for ccTLD registration. In addition, when observing rankings, it is necessary to bear in mind the diversity of existing business models.

Graph 1 shows the performance of .br since 2012.

Graph 1 – Total number of domain registration per year for .br – 2012 to 2020*



**Data in reference to August 2020.*
Source: Registro.br

In August 2020, the five generic Top-Level Domains (gTLD) totaled more than 182 million registrations. With 149.28 million registrations, .com ranked first, as shown in Table 2.

Table 2 - Main gTLDs – August 2020

Position	gTLD	Domains
1	.com	149.279.349
2	.net	13.246.836
3	.org	10.240.183
4	.icu	5.618.105
5	.info	4.298.038

Source: DomainTools.com
Retrieved from: research.domaintools.com/statistics/tld-counts

DO YOU KNOW HOW BRAZILIAN HEALTHCARE FACILITIES REGISTER THE CLINICAL INFORMATION OF PATIENTS? WHAT DATA IS COLLECTED IN ELECTRONIC FORMAT?

Learn about these and other indicators for producing data in the health sector[40], which serves as raw material for Artificial Intelligence applications.

92% OF THE TOTAL NUMBER OF HEALTHCARE FACILITIES **USED THE INTERNET IN THE LAST 12 MONTHS[41].**

OF THESE FACILITIES:

82% HAD **ELECTRONIC SYSTEMS FOR RECORDING PATIENT INFORMATION.**

IN **64%** **CLINICAL AND REGISTRATION INFORMATION IN PATIENT MEDICAL RECORDS** WAS MAINTAINED PARTLY ON PAPER AND PARTLY IN ELECTRONIC FORMAT.

IN **18%** IT WAS ONLY ON PAPER.

IN **18%** IT WAS ONLY IN ELECTRONIC FORMAT.

[40] Based on data from the ICT in Health 2019 survey, by Cetic.br/NIC.br. The indicators refer to the 12 months prior to the survey. Find out more: https://cetic.br/pt/pesquisa/saude/indicadores/.

[41] Of the total number of healthcare facilities.

WHAT DATA ABOUT PATIENTS IS AVAILABLE ELECTRONICALLY IN HEALTHCARE FACILITIES?

[89%] PATIENT DEMOGRAPHICS

[65%] CLINICAL HISTORY OR NOTES ABOUT CARE

[64%] DIAGNOSIS AND HEALTH CONDITIONS

[54%] ALLERGIES

[46%] VACCINES GIVEN

[61%] LAB TEST RESULTS

[53%] LIST OF MEDICATIONS PRESCRIBED

[56%] ADMISSION, TRANSFER AND DISCHARGE

[64%] MAIN REASONS THAT LED TO THE CARE/ CONSULTATION

[51%] NURSING NOTES

[38%] X-RAY IMAGE REPORTS

[24%] X-RAY IMAGES

[45%] VITAL SIGNS

/Credits

TEXT
ARTICLE I
Edson Amaro Jr, Michel Fornaciali, Andre Batista, Murilo Gazzola, Lívia Paiva da Silva, Diogo F. C. Patrão, Marcos Freitas Jr
(Hospital Israelita Albert Einstein - HIAE)

ARTICLE II
Sacha Alanoca, Nicolas Guetta Jeanrenaud, Nyasha Weinberg, R. Buse Çetin, Nicolas Miailhe
(The Future Society)

DOMAIN REPORT
José Márcio Martins Júnior
(Cetic.br/NIC.br)

GRAPHIC DESIGN AND PUBLISHING
Giuliano Galvez, Klezer Uehara, Maricy Rabelo
(Comunicação/NIC.br)

TRANSLATION
Grant Borowik, Isabela Ayub, Maya Bellomo-Johnson, Luana Guedes, Luísa Caliri (Prioridade Ltda.)

PORTUGUESE TEXT EDITING
Mariana Tavares

EDITORIAL COORDINATION
Alexandre Barbosa, Tatiana Jereissati, Stefania L. Cantoni
(Cetic.br/NIC.br)

ACKNOWLEDGEMENTS
Edson Amaro Jr, Michel Fornaciali, Andre Batista, Murilo Gazzola, Lívia Paiva da Silva, Diogo F. C. Patrão, Marcos Freitas Jr (Hospital Israelita Albert Einstein - HIAE)
Sacha Alanoca, Nicolas Guetta Jeanrenaud, Nyasha Weinberg, R. Buse Çetin, Nicolas Miailhe (The Future Society)
Eneida A. Mendonça (Indiana University / Regenstrief Institute)
Bernardo Mariano Junior (World Health Organization – WHO)

United Nations Educational, Scientific and Cultural Organization

Regional Centre of Studies for the Development of the Information Society under the auspices of UNESCO

Brazilian Network information Center

Brazilian Internet Steering Committee


STRIVING FOR A BETTER INTERNET IN BRAZIL
CGI.BR, MODEL OF MULTISTAKEHOLDER GOVERNANCE
www.cgi.br
nic.br cgi.br
FOTOS: RICARDO MATSUKAWA E SHUTTERSTOCK