All models are wrong, but some are useful: mathematical models at the time of Covid-19

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ABSTRACT

Epidemiological models have been crucial tools throughout all stages of the 2020-21 Coronavirus pandemic: using promptly available or historical data, they have studied and tried to anticipate its progression, providing valuable guidelines for public health officials, policymakers, and other medical and non-medical audiences. While useful, models are not designed to be infallible, and for this reason, they have been frequently subject to criticism. There is a discrepancy between what models do and how they are presented and perceived. Several juxtaposing factors, including current beliefs about scientific reliability, the role of quantification, and the epistemic values grounding the field, are at the core of this discrepancy. While scientific literacy may play a role in addressing this discrepancy, analyzing and becoming better aware of these factors may suggest long-term strategies to address, acknowledge, and communicate the pandemic's inherent complexity and stochastic qualities.

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1. Introduction

In an opinion piece in the Canadian newspaper *The Globe and Mail*, Kumar Murty, Director of the Fields Institute for Research in Mathematical Sciences (Toronto, Canada), reflected on the increasing visibility of mathematical models. Before the pandemic, models were mainly unknown to the general population outside of science and mathematics circles. Fast forward to March 2020, and they have become a daily view, dominating the news on some occasions, especially when their publication ought to influence public policies and other critical collective decisions (James et al. 2021; Murty 2021).

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Mathematical models have been crucial tools throughout all stages of the pandemic: using promptly available or historical data, they seek to explain a phenomenon and to study how different factors affect its course. In the case of the coronavirus pandemic, mathematical models strive to study its progression, to anticipate or prevent possible scenarios, and to warn about the dangers and benefits that certain behavioral modifications and policy adoptions could have on its unfolding. Policymakers and administrators have often turned to modelers to help them decide whether to reopen businesses and schools or adopt or relax safety measures (Cepelewicz 2021). Models are frequently the subject of criticism: some controversial models, for instance, have led to disastrous decision-making. Others were "deemed unreliable or inherently flawed" (Holmdahl and Buckee 2020) and were accused of providing numbers that later turned out to be inflated or exaggerated (Murty 2021).

Epidemiologists and modelers are well aware of the inability of models to provide complete and accurate predictions. Adam Kucharski argues that a model "is just a way of understanding a particular process or a particular question we're interested in. The point is to understand what is the trend, what is the qualitative take-home message you get from this" (Cepelewicz 2021). Murty warns that models "are not perfect because they are designed to fit a particular epistemology, and they are not perfect because the spirit of science is not about exactitude but experimentation" (Murty 2021). According to Timothée Poisot, models are "a little bit like fables…[They] are tools to help us think generally about how infections spread, not tools to help us predict"(Poisot 2020).

These positions are not uncommon among the mathematics and modeling community. Famously, "all models are wrong, but some are useful" is an aphorism uttered on several occasions in the seventies and eighties by statistician George Box to point out that it is not the exact result that counts the most in a model, but how useful it is to help understand a phenomenon (Box 1976). However, when models emerge in the public domain and become instrumental in making crucial life-saving policy decisions, their quantitative content, not their qualitative usefulness, is most valued. When they go public, models are (and must be) presented as reliable. Then, when reality does not match the predictions, criticisms turn into a complete lack of trust (Holmdahl and Buckee 2020; Tufekci 2020).

There is no doubt that instrumentalization and politics, on the one hand, and scientific illiteracy, on the other, contribute to creating a discrepancy between what models do and how they are presented and perceived. However, this same discrepancy also signals an epistemic tendency to overemphasize the role of quantification in dealing with the pandemic. Realizing that quantified content is ineffective in tackling such a complex issue may intensify the general sense of uncertainty that has already dominated the current situation. When this discrepancy becomes exposed, it reveals how current beliefs and assumptions about scientific reliability are caused by many juxtaposing factors, not just by whether or not a model is correct. These factors are all equally contributing to fueling or dissipating uncertainty. Analyzing this discrepancy may suggest few long-term strategies to address, acknowledge, and communicate the pandemic's inherent complexity and stochastic qualities.

2. Modeling: a risky business

In her popular book *Weapons of Math Destruction*, Cathy O'Neil explains that modeling is a mental exercise we all do daily: based on specific parameters and experience, we anticipate potential scenarios and act upon them (O'Neil 2017). These scenarios may or may not self-realize, as several unknowns may intervene to change each situation. In an interview, she explains: "a model takes in data … and trains to learn to seek patterns. And then the model becomes a way of predicting" (Sonnad 2016). According to Metcalf et al. (2020), mathematical models "can be used to estimate parameters of pathogen spread, explore possible future scenarios, evaluate the efficacy of specific interventions retrospectively, and identify prospective strategies." To achieve these results, parameters, Subramanian and Kattan (2020) explain, "require a number of assumptions to be made," that is, speculations regarding population behavior and mobility, virus' Ro, disease incubation and length, and many other quantifiable values and inputs.

In the classic SIR model (or compartmental model) and its many variations, the arc of a pandemic is based on three types of populations: the Susceptible (the individual who could contract the virus), the Infectious (the already-infected or potentially infected individual informing the rate of spread) and the Recovered (the one who is no longer contributing to the spread, because they are either vaccinated or dead). The more variables we introduce, the more complex the model becomes. For instance, in the agent-based or individual spread model, the individuals' infectivity and exposure depend on whether they infect family, colleagues, people they meet in public, or during other random occasions (Hoertel et al. 2020). When people are represented in a network model, individuals are treated according to graph theory. Instead of being 'hosts' and 'contacts,' or 'actors' and 'relations,' they become nodes and edges in a complicated lattice: "In each case, it is the presence of a relationship between individuals in a population that is the issue of concern" (Keeling and Eames 2005).

It is important to remember that although sometimes very accurate, epidemiological models – especially when they contain a considerable number of historical data – are simulations. They propose a 'what if' scenario based on what is currently known. Not unlike bacteria studied in a controlled environment such as a petri dish, a population is evaluated according to a set of established – though constantly growing and diversifying – parameters. Even when these parameters are fed into an AI system, many unknowns are unavoidably left uncovered. Models are not just to make exact predictions but to persuade, especially during circumstances such as a pandemic (O'Neil 2020), where the

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resulting predictions are meant to convince a school or a government to pass new regulations, to modify one's behavior to suit, or to change course from, the prediction.

This is what happened in mid-March during the early phase of the pandemic when a research team at Imperial College London used an agent-based model to convince governments that refusing to implement any form of quarantine would have had disastrous consequences. Its projection predicted up to half a million deaths from Covid-19 in the United Kingdom alone and 2.2 million deaths in the US if nothing was done to mitigate the spread (Ferguson et al. 2020: 9). The model was not supposed to provide exact numbers but to persuade policy-makers to act urgently (Cepelewicz 2021). As a result, British Prime Minister Boris Johnson almost immediately announced stringent new restrictions on people's movements. The United States announced social distancing rules soon after (Adam 2020). Similarly, in 2021, models released by the Ontario Covid-19 Science Advisory Table were used to prolong the lockdown in specific areas of the province most severely hit by the B.1.1.7. variant of concern (CBC News 2021).

Policymakers and governments maintain a relative trust in models. Of course, until they fail. Trust quickly turns into criticism when the numbers predicted by these models look inflated or don't match the expectations. If the projection were proved correct, it would mean that it has failed to persuade (Cepelewicz 2021). Models like the one produced at the Imperial College were picturing a purposely exaggerated doomsday scenario. In this case, because governments took precautions, cases and death ended up less numerous than expected.

Outcomes do not always turn out better than expected. When the projections produce unexpected adverse consequences, criticism leads to mistrust or outmost rejection of the modeling practice, threatening its value and validity. The unfortunate failure of the model created at the University of Illinois at Urbana-Champaign (UIUC) is a case in point. To preserve the safety of students and staff as they were returning to campus, physicists Nigel Goldenfeld, Sergei Maslov, and their research team created a networked-based predictive model, which they complemented with frequent Covid-19 tests and – they assumed – strict surveillance strategies. The primary purpose of the model was not to make precise predictions but to help administrators make informed choices on the best way to allow classes and other activities to resume safely and smoothly (Chang 2020). The result was a complex and expensive operation: 40,000 students were asked to take specially designed fast-diagnostics saliva tests twice a week (the university paid $10 each). In addition, students had to register for a contact tracing app: if their test turned positive, they would lose access to the university buildings and would have to be confined to their dorms. Despite the current social distancing restrictions, the model had even introduced a variable anticipating that more than 7,000 students would go partying three times a week (Nadwordny 2020).

However, mere weeks after the opening of the campus, it became clear that the model had failed. In trying to contemplate all the possible variables, the two scholars and their interdisciplinary team had assumed that students would follow the recommendations established by the university administration. Even though they knew that students are notorious for breaking the rules, they did not anticipate that several would continue to go to parties even after testing positive. Some of these students even "tried to circumvent the app so that they could enter buildings instead of staying isolated in their rooms" (Chang 2020).

As a result, the model could not predict the speed at which (infected) students would spread the disease among their (susceptible) peers, compromising the validity of the simulation and leading to dramatic real-life results. Cases immediately grew exponentially, reaching in one week the numbers that had been estimated for months later. Several media outlets and skeptical critics, and (especially) flat-out anti-science politicians read this case as one more reason to mistrust all models and ultimately all scientific projections (Cepelewicz 2021).

During the past 15-18 months, people worldwide have been caught in a constantly changing, fast-paced, and intense flow of information. They believed that reliable models turned controversial and/or inaccurate; doomsday scenarios have not (or not entirely) self-actualized; competitive models have sometimes provided opposed outcomes. A flood of contradictory information originating from news, social media, and other – often questionable – sources have made the already unstable situation even messier. In the examples above, mathematical models have functioned to bring some temporary certainty to an uncertain future by quantifying this future. In other words, they tried to "…turn the variability that we see in the world into a tool that can quantify our uncertainty about facts and numbers and science" (Roberts 2020). While quantification is unlikely to bring indisputable results and eliminate all unknowns, it does indeed create a false, if a temporary sense of certainty, obtaining a considerable degree of comfort. However, during the pandemic, the confidence created by facts and numbers was short-lived and hasn't satisfied the public need for certainty. Who to believe? What to make of the tentativeness of mathematical models vis-à-vis claims to their accuracy? And how is uncertainty generated and aggravated?

3. Uncertainty and data

The cases above offer a fascinating window into how institutional science and the public carry similar preconceptions about what science does, what accounts for reliable evidence, and what is worth trusting. It would be easy to dismiss the complicated public reception of mathematical models as symptoms of a lack of understanding of

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science or scientific literacy. Since models are also instruments of persuasion, the circumstances that prompted their creation (i.e., the urgency to persuade policymakers to implement specific rules) utilize cues that the public, policymakers, and scientists value equally. Interestingly, the very elements that are most likely to generate confidence are also the ones causing skepticism.

Epidemiological models emphasize quantification because it is collectively interpreted as superior and more persuasive than simple verbal recommendations. The general belief is that science is "a monolithic collection of all the right answers" (Roberts 2021). The so-called "right answers" here come in the form of statistical data, big data, and algorithms. The problem with mathematical models is twofold: first, although they contain all the above elements, which in the eyes of the public and many data lovers constitute the perfect examples of successful quantification; they also have errors and elements that cannot be easily predicted (Metcalf et al. 2020). In addition, models may use different datasets, quickly changing datasets to reflect new findings, or datasets that are not entirely reliable (Griffin 2020). These are not severe problems if they lead to constructive critical reflections on the role of projections and their helpful message. However, in most cases, errors and discrepancies are treated with immediate criticisms and harsh attacks.

Second, to produce models, scientists must utilize measurable and accepted parameters. However, epidemics and outbreaks are determined and transformed by many factors and behaviors complicated by many variables or cannot be anticipated. For instance, while human behavior can be interpreted and simulated, it cannot be precisely predicted, partly because individuals' reaction to outbreaks and health emergencies depends on their personal and collective circumstances, health condition, socio-economic status, age, etc. The failure to predict irresponsible student behavior at UIUC is a clear example. Furthermore, it was only when racial and ethnic minorities in the United States (first African American, then Latinos) were found to be three times more likely to be infected and gravely impaired from Covid-19 than other people that the trend was more closely studied (Strings 2020).

Models use parameters commonly accepted as relevant by the medical community. For example, "long-Covid" has been one of the most challenging phenomena to track during the pandemic. The so-called long-haulers are Covid patients, who, in increasing numbers, suffer from lingering and often life-altering symptoms weeks and even months after official recovery (Barber 2020). In addition to being a condition that can vary dramatically in length and intensity from individual to individual, long-Covid was mostly considered a rare occurrence. Importantly, although these patients suffered debilitating symptoms, their condition was not regarded as acute. As well, they were no longer infectious. Thus, long-Covid was not included in any epidemiological model (Rubin 2020). It was neither quantifiable (because so diversified) nor deserving the same attention of death and hospitalization cases.

As Fulvio Mazzocchi reminds us, "…the emphasis on numbers and data—which can be seen as collections of facts (e.g., values or measurements)—is another way to frame the notion or myth of the objectivity of scientific knowledge. It seems like an attempt to find in computational power what we have not found in human cognitive abilities" (Mazzocchi 2015). The belief that facts and data provide objectivity and exactness has its origins with the scientific revolution and continued throughout the enlightenment, finding confirmation with the advent of cybernetics and Artificial Intelligence. During this long period, deductive reasoning, characterized by hypothesis-driven, theoretical research seeking validation, was contrasted and gradually challenged by empiricism, a form of inductive research based on experimental data instead of preconceived theories. Yet, deductive and inductive research are complementary, and the practice of mathematical modeling is a testimony to this coexistence.

Rob Kitchin notes that an inductive strategy of identifying patterns "does not occur in a scientific vacuum but is discursively framed by previous findings" (Kitchin 2014). Many of the mathematical modeling exercises that we see today improve one progenitor SIR model conceived by Kermack and McKendrick (Kermack et al. 1927) almost one hundred years ago. Although finding patterns and correlations play "an important role as heuristic devices…they have to be further analyzed — using models and experiments to assign them a meaning and to distinguish between meaningful and spurious correlations" (Mazzocchi 2015). In other words, data are not "out there." Although the process of model building is driven by the large amount of data produced and is less dependent on theoretical presuppositions or hypotheses, it is still informed by epidemiological principles, research objectives, previous theories of contagion, and assumptions about human behavior. The parameters used in today's Covid-19 models are mainly based on fixed and historically established values. In addition, they are selected to draw hypothetical scenarios to help policy decisions and behavioral recommendations: this means that their focus tends to lie on acute cases, that is, those cases that could cause sudden medical infrastructure overload or economic breakage.

Today, we are experiencing the culmination of inductive reasoning due to the rise of big data. Instead of acknowledging the role of theory as the foundation (or the objective) of induction and the import of assigned values in shaping epidemiological models, this new wave of empiricism prioritizes data and their correlations as the sole principle for understanding all phenomena. In his widely quoted and much-debated article "The End of Theory," Chris Anderson argues that "rather than testing a theory by analyzing relevant data, new data analytics seek to gain insights 'born from the data'" (Anderson 2008). The collection and processing of these data are brought to us today thanks to an increasing degree of mechanization of technologies, such as high-powered computation and new analytical techniques. In turn, the mechanization of data collection strengthens the assumptions that data are neutral, comprehensive,

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and more accurate. This gives the illusion that data "speak for themselves," that is, large quantities of data, on their own, will be able to provide answers about the world without the need of theorizing it. In reality, data collection is never neutral ut reflects "the technology and platform used, the data ontology employed and the regulatory environment, and it is subject to sampling bias" (Kitchin 2014).

The end of theory claim supported by Anderson is reflected in the way mathematical models are perceived. Of course, the collection of data is not merely an empirical activity. Science does not collect data randomly as "experiments are designed and carried out within theoretical, methodological and instrumental limitations" (Mazzocchi 2015). However, the theory of contagion, the theoretical speculations supporting the model, and the lessons (theoretical or practical) it proposes, are pushed to the background when introduced publicly: what counts are the predictions based on the data used to create the model. It is precisely because of the assumption that data can produce the answers on their own and free of bias that the mathematical model, when it doesn't live to its expectations, is more likely to create surprise and disappointment and become the easy target of accusations of manipulation and incompetence.

4. Modeling and the Unknown

The deep sense of uncertainty that the pandemic has precipitated has put unfair pressure on the model as a reliable tool. Its self-imposed confidence creates an initial degree of comfort until – like everything else in the pandemic – it turns into something that can't, or can only partially, provide indisputable answers and clear guidelines. Modeling, although helpful, is then seen as a failure because it does not perform as expected. This leads to rejection and counterproductive reactions.

During a public outreach workshop on modeling, mathematician Deirdre Haskell explained how the recent models published work today. Models have reached such complexity that it is tough for a non-mathematician to "distinguish the forest from the tree" (Fields Institute 2021). However, all mathematical models tend to all stem from relatively simple and easy to explain formulas. Therefore, the resulting general lack of understanding of mathematical models points to a need for better science and mathematics literacy. The relative simplicity of their foundation suggests that better descriptions and explanations of the numbers and the graphs published periodically would go a long way in enhancing such literacy. However, since both the public and the modelers share the same general principles of validating scientific knowledge, they end up confirming – or becoming complicit in – the old rhetoric that attaches exactness to numbers and bias to discourse. In other words, neither the public nor the scientists acknowledge the flaws of mathematical models as quantitative tools. At the same time, the qualitative values that models represent and the significance they carry as non-quantitative guidelines are often ignored or underestimated.

Siobhan Roberts refers to the general "uncertainty about facts, numbers, and science" that we are experiencing today with the pandemic as epistemic uncertainty (Roberts 2020a). Navigating a sea of unknowns and dealing with unexpected outcomes is how science has always functioned and is at the center of experimental practice. However, scientists may be reluctant to publicly admit to the inherent uncertainties that prevent them from giving exact solutions. Many fear that being honest will discredit their work, falling again for the belief that science, and its quantified rigor, will provide the correct answer. Roberts suggests that admitting the imperfection of science in general and mathematical models, in particular, may create a healthier relationship between the public and science. A study from Cambridge University on uncertainty has concluded that "people have a positive reaction and trust information more when the communicator is being open about uncertainties in facts and figures" (Roberts 2021).

Although I generally agree with Roberts' argument and its potentials, I suggest that we further unpack how epistemic uncertainty operates. In fact, during the pandemic, being honest about the possibilities or the partial failure of a mathematical model may still not be persuasive enough to a public accustomed to more assertive tones. It takes time for a cohort used to listening to reassurances, answers, and specific recommendations to accept uncertainty. The public is still searching for clear guidelines at this point. Yet, honesty could become a long-term solution to transform how the public listens to and trusts science eventually.

For instance, recent statements issued by the Canadian National Advisory Committee on Immunization (NACI) regarding the safety of the Astra Zeneca vaccine, after thousands of eager individuals had flocked to the pharmacy to receive their first shot, caused countless debates in the news and on social media. Anxiety had spiked among the population of Ontario after a less than successful vaccine rollout was accompanied by a rapid rise of cases of coronavirus variants of concern (VoC). In March 2021, the province of Ontario went into total lockdown. To ease the pressure on overwhelmed hospital ICUs, and to facilitate immunization as quickly as possible, NACI and other public health agencies advised the public to take the first, and at that time most readily available, vaccine, Astra Zeneca. This recommendation was made upon considering that even though the vaccine had been known for causing very rare blood clots in specific individuals, data about the current situation indicated that the benefits surpassed the risks. Eligible individuals were quick to follow the suggestions. However, as the hospital bed situation improved and new data about vaccine side effects and safety had become available, NACI posted another statement, this time indicating that "The benefit-risk analysis determines that the benefit of earlier vaccination with the viral

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vector Covid-19 vaccine [Astra Zeneca] outweighs the risk of Covid-19 while waiting for an mRNA Covid-19 vaccine [Pfizer and Moderna]" (Public Health Agency of Canada 2021). Many concerned individuals were alarmed by a statement indicating that mRNA vaccines were preferred and voiced their disappointment: not only had NACI somehow changed their preferences, but they also had only decided to warn, rather than reassure the public about the vaccine side effects (Jee-Yun Lee 2021; Rabson 2021).

The announcement was welcomed with panicked reactions and accusations of incompetence, not because the statement was or was not true, but because NACI had not provided clear guidelines about further actions. In fact, despite the existence of widely available data on vaccine side effects since early vaccine rollout in Europe a few months before (Mahase 2021), and the abundance of information, complemented with statistics, describing the risks, the public in Canada had generally trusted public health and followed their recommendation. Now new data seemed to download responsibility upon the people rather than rely on orders was deemed inconceivable. Further criticism was voiced later when it was left to the public to decide whether to match different vaccines or continue with the same (while knowing the risks), as concerned individuals vented on social media about the ambiguity of communication and the lack of clarity provided to the public (Menaka Pai 2021).

One factor that complicates the understanding of models and creates more uncertainty is their temporal variance. To understand the function and behavior of SARS-CoV2 – a novel coronavirus that is a virus we knew little about before it emerged in December 2019 – science is constantly upgraded and redacted. This factor is unfortunately aggravated by the tendency of the public to hang on to early findings rather than to embrace changing situations (Connecticut Public 2020). Retracting obsolete information or even preventing it from being recirculated repeatedly is equally tricky, even though "a key responsibility of any journal is to correct erroneous information that it has published, and as quickly as possible" ("Retraction Challenges" 2014). New evidence is released quickly and often as pre-print, causing older and more recent findings to coexist, sometimes side by side. The significant quantities of models circulated today correspond increasingly rich and constantly transforming datasets.

Relatively simple data have been complicated with more variables and hypotheses, as old theories have been debunked and new findings have been gradually incorporated. For example, models had to be changed to accommodate new medical and infectious disease data; non-medical interventions such as the obligation to wear masks and vaccine rollout have all been introduced. As Zeynep Tufekci points out, "model-makers have to work with the data they have, yet a novel virus, such as the one that causes Covid-19, has a lot of unknowns" (Tufekci 2020). Not only did the early models only contain a limited amount of data coming from the countries that had recorded the first outbreaks, allegedly Italy and China, but these data were often inaccurate, either because of a lack of transparency from the governments or because of lack of tests and insufficient surveillance prevented accurate counts. In addition, data related to the means of transmission (droplets or airborne?) and modes of protection (are masks useful?) were not accounted for in the early phase (Yong 2020). As newer models benefited from richer and better data, human errors (like the one inadvertently committed by Goldenfeld and Maslov at UIUC), and new findings, later simulations need to account for additional unknowns as potential transformative factors. From here, building increasingly complex and comprehensive mathematical models on time has become crucial.

During the Covid-19 pandemic, the flow of information has been intense. In addition to sparse and ever-changing data, transforming science, and a steep medical and scientific learning curve, political agendas and narcissistic personal goals created an explosive cocktail of misinformation and disinformation, contributing to uncertainty in significant ways. Armchair epidemiologists with data science experience but little epidemiology knowledge would generate their models and data visualizations, publishing them on opinion platforms such as Medium or disseminating them on social media. While there is nothing wrong with engaging with the data available, these self-published individuals labeled themselves as experts, assuming competencies they didn't have. Missing real experience and knowledge in epidemiology, their products contained frequent mistakes or provided misleading analyses (Muir 2020). As Poisot observes, "these models are not wrong." They are that special brand of 'correct' that simply does not translate into 'useful,' which is arguably the point of most mathematical models" (Poisot 2020). In addition, since the very start of the pandemic, social media have become the preferred repository for conspiracy theories, contrarian theories, and other unproven news that would equally confuse naive and experienced readers. The amount of inaccurate and manipulative information was so diffused that the World Health Organization (WHO) declared that they were fighting two battles: one against the pandemic and one against the infodemic (Caulfield 2020; Muir 2020).

A seldom mentioned factor in the propagation of uncertainty is a personal and collective experience. Quarantine and physical distancing fatigue, paired with changing recommendations, have made even the most informed individual undecided and insecure about the integrity of mathematical models and the honesty of public announcements or the implementation of general measures. Depending on personal and social circumstances, attitudes towards models have been swinging between blind and hopeful reliance on [the god] model to complete disregard and disbelief for its predictions. These aspects are never considered when analyzing pandemic perception and trust in science. In many cases, those individuals maintaining skeptical opinions regarding models are not necessarily anti-science, poorly educated, or manipulated by conspiracy theories: they are simply concerned and probably very anxious about the uncertainty of the pandemic: anxiety paralyzes.

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5. Conclusion

Among the many unknowns and twists we have seen during the pandemic, mathematical models have found themselves at center stage for the helpful guidelines they provided with their projections but have often been blamed for their errors and lack of accuracy. Yet, models are not the only contributors to the deep sense of uncertainty we are experiencing today. The spread of a novel virus made it difficult to build models and predictions from the limited and non-existing data available at the pandemic's beginning. The pace of discoveries and evidence emerging and the variables to be accounted for as the pandemic expanded were equally challenging to monitor. Furthermore, while the mistakes and erroneous projections led to disastrous outcomes and human loss, the overlapping of new and old data, misinformation and disinformation, scientific illiteracy, and hubris threatened to lead to equally damaging consequences.

Since the beginning, several obstacles have complicated the understanding of the pandemic without doubting the veracity of the information being disseminated or the motives behind its dissemination. Epidemiological models have come under particularly harsh criticism in this condition of many unknowns because they initially assumed absolute trustworthiness. The fact that these models are presented as accurate is both an obligation to conform to and an implicit acceptance of a given system of beliefs. Despite or because of their illiteracy, the public is trained to trust information packaged in a quantified form.

Although we are still operating with solid beliefs about the superiority of quantified information, the fallibility that mathematical models have demonstrated may lead to epistemic transformations and to adopting different approaches to help better comprehend complex phenomena such as pandemics. On the one hand, the current belief system prefers, even requires, that solid language be used over tentative and non-incisive statements. The current social media battleground's risk is to favor informed and misleading inadvertently– yet well distributed and well packaged – sources. On the other hand, honesty and transparency can encourage a healthy debate and a gradual change in the very epistemologies underpinning the science of modeling and how it is generally understood.

There have been a few notable cases championing new approaches. For example, the model created by ecologist Madhur Anand and mathematical biologist Chris Bauch combined two types of models: an epidemiological model of virus transmission and a "game-theory model, [which] factored in human behavior and drew on Google data that revealed who went where and when in Ontario from March to November" (Roberts 2020b). Specifically, the model applied the prisoner's dilemma game to model how, during the pandemic, individuals exercise their choices by weighting them against the choices made by others. The model studied how human behavior could transform the course of the pandemic in the presence of higher vaccination rates and non-pharmaceutical interventions (Jentsch et al. 2020). While this model emphasized the relational nature of the pandemic, by treating human behavior "as a flux and as a set of dynamic exchanges, rather than a constant" (ibid.), the categories and inputs it employed remained unchanged. Thus, the model is innovative in processing information, but not how it is collected and classified. However, it is still an important example, expressing the need to acknowledge the dynamics of pandemics and the importance of looking outside of traditional modeling paradigms and disciplinary constraints to understand complex phenomena.

All in all, while the latest modeling efforts (including Anand and Bauch's) do not represent a radical transformation in the way science and the public value quantified data, they voice an urgent need for newer analysis that is not limited to what newer technologies and data processing can do. Instead, it focuses on reflecting on and transforming the principles, values, and parameters comprising them. To accomplish this task, we must engage in an increasingly interdisciplinary discussion that equally emphasizes quantified information and qualitative discourse.

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