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In Search of an Integrated Corona Knowledge Ecosystem for Actionable Health Policy – A Mind Mapping Voyage and an Exploratory Decomposition in Spatial Pandemetrics*

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Abstract

This paper seeks to map out the knowledge requirements and infrastructure needed for a comprehensive and quantitative analysis of the societal and geographical dimensions of effective policies regarding COVID-19 ('coronametrics' or 'pandemetrics'). After a sketch of limitations and challenges in corona research, a multi-layer mind map is designed in order to systematically scan the cognitive needs in the corona domain and to address both health policy and socioeconomic-medical information requirements in a geographic context, with a particular view to the use of actionable dashboards. A systematic decomposition of the corona knowledge system is pursued to acquire a coherent insight into gaps in corona knowledge, with particular emphasis on policy and research relevance. It turns out that the study of causality patterns in the complex space-time evolution of COVID-19 is the Achilles' heel in the analysis of pandemetrics and calls for new effective and preventive research endeavors in support of actionable health policy.

Keywords: mind map, COVID-19, immunity, corona dashboard, corona arena, decomposition, coronametrics, pandemetrics.

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1. Scope and aim

The global rapid rise of COVID-19 has been one of the most serious concerns in public policy over the past years (Barrett and Poot, 2023). Fortunately, after more than three years of corona virus infections, the contagion trajectory of COVID-19 seems to be nowadays on a final downturn in most countries, with small uprises here and there of new, but less harmful corona variants. Medical science has clearly been rather successful in coping effectively with this contagious disease, which has caused the loss of so many people, ranging from 20.000–25.000 people in a country like the Netherlands to millions worldwide. Notwithstanding the great achievement of medical-pharmaceutical science to develop effective vaccines, several serious scientific and policy questions remain, in particular:

- *medical/pharmaceutical questions* such as: the initial source(s) of the corona virus, its differential spread pattern (space and time), the vulnerability of specific population groups, the development of (herd) immunity against the corona virus, the impact and use of different types of vaccines (and their booster complements) in different countries, as well as the effectiveness of various pharmaceutical and non-pharmaceutical policy intervention measures.
- *socio-economic and spatial impact questions* such as: the impact of socio-economic status and education on corona infections, the implications of social and interactive behavior of people (e.g., handshaking, social distancing), the effect of online working and shopping modes (including lockdowns), the degree of physical intensity of social interaction among various people, the preventive or protective effect of active micro-mobility (e.g., walking, bicycling), or the rising enjoyment of green or blue natural environments.

In addition to these causal infectious disease questions (which need thorough empirical data and evidence-based research, on both medical and socio-economic/cultural-geographical dimensions), there is now also a rising interest in important long-run and strategic questions, such as:

- *medical-pharmaceutical*: stimulus-response questions on the time pattern of the spread of COVID-19 (i.e., space-time medical geography), the underlying causes of the origin and contagion spread of the corona virus with different waves, the long-run causes, and implications of long COVID, etc.
- *socio-economic and spatial*: impacts of mobility patterns (commuting, shopping, education, family visits etc.) on the spread of COVID-19, the economic consequences of COVID-19 for mobility-rich economic sectors (e.g., tourism), the distinct effectiveness of different corona measures and policies in different countries, the identification of vulnerable groups (e.g., cultural, low-income, low-education), or the impacts of high densities, climatological conditions or unhealthy environments in big cities on the occurrence probability of COVID-19.

The COVID-19 pandemic has thus prompted a range of research challenges in different fields, not only in the medical-pharmaceutical field, but also in the social science field, e.g., geography, economics, psychology, sociology, administrative sciences, law, and data science (e.g., Farca and Dragoș, 2020). From both a retrospective learning point of view and a prospective predictability point of view, there is a clear need for an evidence-based knowledge exploration of causes and impacts as well as of space-time patterns of the COVID-19 pandemic. This quantitative analysis of pandemic phenomena in a space-time context may be called *coronametrics* or – in a more general sense – *pandemetrics*, which is a cross-disciplinary quantitative (data-based, statistical and econometric) approach to the investigation of pandemic phenomena ranging from local to global levels. In so doing, we need extensive and reliable databases on all aspects of the corona phenomenon.

We also note that the corona crisis has brought to light a major weakness in public health policy, regarding the presence of heterogeneous or sometimes contradictory information and communication, which has led to an erosion of trust in governments. The pandemic has created a great deal of uncertainty among the broader public, due to incomplete and sometimes less transparent or less reliable information on the many aspects related to the sources, transmission, geographical spread, risks, preventive actions and medical consequences of COVID-19. Since the outbreak in 2019 much new information on the complex force field of this pandemic has come to the fore, but a clear comprehensive picture of its multi-faceted mechanism over time and space is still largely missing. The present paper seeks to lay the foundation for an evidence-based *mind map* based on multi-layer decomposition that depicts the various forces at work. This comprehensive image of the COVID-19 arena is not only useful as a testable communication tool for citizens' engagement and stakeholder confidence in policy measures regarding the control of the corona virus, but is also an empirical tool for understanding and managing the spread of the corona virus (or other pandemics) and for building an effective defense wall against an unlimited dispersion of the virus.

The corona mind map is in this study thus not only an information tool, but serves also as an interactive communication tool with both citizens and medical health authorities. A core element of the corona mind map is formed by a combined *scorecard* and *dashboard* on corona cases (including hospital admissions and death tolls), not only at national level but also at regional and local level. The study aims to present a quantitative open-access corona information-communication system, in which in addition to external and personal vulnerability conditions, also the evolution of vaccination rates, immunity rates, government (pharmaceutical and non-pharmaceutical) intervention measures, and human response mechanisms (e.g., social distancing, mobility and physical interactions) are taken into consideration. It seeks to trace the knowledge needed for a systematic understanding of the corona contagion.

The empirical data used in our study comprise *inter alia* public health data, vaccination data, policy stringency data, Google mobility data, and local COVID-19 data. The database is based on open-access and public space-time information since the beginning of the pandemic, and covers not only macro data, but also whenever possible detailed relevant space-time local data. The mechanism of this interactive corona communication instrument – including policy and behavioral response mechanisms – is illustrated for the space-time trajectory of COVID-19 in the Netherlands by means of open-access decentralized corona scoreboards and dashboards, which contribute to a focused research framing.

There is indeed a wide-ranging research agenda which calls for evidence-based exploratory and causality research that maps out the complex corona force field. The present study will present a *multi-layer* (*cascadic) corona mind map* that seeks to offer a simplified but structured image of the 'corona arena'; it is built up in a stepwise way (*decomposition*), where each of the building blocks represents an important knowledge domain to be covered for a full understanding of the corona phenomenon. Thus our aim is to explore and map out critical knowledge questions by employing a stepwise mind map for scientific and policy answers, at the level of both an integral corona perspective and a decomposed perspective for each of the building blocks of the overall mind map.

This paper has the following structure. After the above-described introduction to the challenge of studying the geography of the corona virus, we will offer in Section 2 a concise review of challenges in spatial corona research, with a particular view to the relevance of coronametric (or pandemetric) research in the post-corona time, while we will also provide a concise and selective overview of some relevant coronametric studies. The complexity of the corona field leads us to the design of a simple but organized *corona mind map* in Section 3, which will be further specified in an operational *corona arena image*, which forms the foundation for our knowledge framing exercise. This corona arena image is in Section 4 decomposed into six corona *knowledge domains* which act as a framework for distilling and specifying quantitative research questions in a geographical or spatial context. The information from the previous sections will be empirically illustrated by means of a large database from the Netherlands in Section 5, which highlights the need for a corona science agenda to be used for policy and scientific purposes. Finally, Section 6 offers concluding remarks.

2. Understanding the corona spectrum

COVID-19 has shown a world-wide coverage since its first appearance in the end of 2019 in Wuhan (China). Its spatial dispersion pattern follows a typical epidemiological space-time curve all over the world. However, it is characterized by a high degree of heterogeneity with a clear geographical disparity in various parts of the world. The spatial disparity in COVID-19 cases does not only manifest itself at a cross-country level (for instance, New Zealand vs. Italy), but also at regional or urban level (for instance, densely populated city centers vs. green suburbs). Furthermore, the time pattern of COVID-19 also displays clear features of differential dynamics, with different waves of intensity and amplitude in different parts of the world. Consequently, a range of important spatial knowledge questions on corona has arisen (see e.g., Couclelis, 2020; Sassen and Kourtit, 2022; Bouzouina, Kourtit and Nijkamp, 2023; Celbis, Kourtit and Nijkamp, 2023), which altogether comprise of a multi-faceted spectrum of facts, ideas and assertions on COVID-19.

In simple terms, one might describe the corona spectrum as a chain from genesis through intermediate mechanisms to final outcomes, in a way comparable to the typical design of a standard chain-integrated transportation model. Such a chain may contain *inter alia* the following successive components:

- COVID-19 generation (e.g., place, time, origin);
- spread of corona virus (e.g., distribution, spread channels);
- geographical destination of and exposure to corona virus (e.g., destination countries, social contacts, mobility modes);
- susceptibility of specific groups (e.g., vulnerability, age);
- local infection occurrence and treatment (e.g., external conditions like weather, quality of medical system);
- regional hospital intake (e.g., intensive care, capacity);
- acceptance of vaccination programs (e.g., type of vaccines, sequence);
- immunity development (e.g., natural immunity, pharmaceutical immunity);
- local and national government intervention measures (e.g., lockdown, facemasks);
- behavioral responses (e.g., social distance, green behavior);
- spatial mobility effects (e.g., transit behavior, home office);
- socioeconomic implications (e.g., labor market, online shopping);
- social and psychological effects (e.g., well-being, mental health);
- spatial implications (e.g., recreation, urban healthcare planning);
- preventive measures (e.g., social density, medical testing);
- post-corona society (e.g., leisure, home office); etc.

The various dimensions of COVID-19, as exemplified by the above somewhat arbitrary list of successive focal points to be addressed, can be summarized in three stages of scientific interest from the perspective of spatial pandemetrics. This triple-stage constellation comprises:

1. the *corona genesis*: the geographic seedbeds and channels shaping the rise and transmission of COVID-19;
2. the *corona fabric*: the mechanism of intervening and moderator factors (medical, behavioral, urban, transportation, regulatory) that determine the space-time corona dynamics;
3. the *corona impact assessment*: the quantitative study of the socioeconomic, behavioral and health care effects of the COVID-19 infection pattern and of related policies.

It goes without saying that for the quantitative study of these three domains advanced statistical and econometric tools are needed, ranging from traditional multivariate techniques to advanced deep learning approaches. Hence, coronametrics or pandemetrics is becoming an important research field in the social sciences.

Over the past years, an avalanche of publications on corona issues has been published in many disciplines. A series of econometric models and statistical analyses have come to the fore in order to offer a quantitative understanding of the spatial complexity of the occurrence and spread of COVID-19. Some selective examples of such quantitative contributions are:

- Simulation modelling and scenario assessment of COVID-19 (see e.g., Bordehore *et al.*, 2020);

- COVID-19 effect studies on labor markets (see e.g., Kapas, 2022);
- Spatial autocorrelation analysis of the spread of COVID-19 (see Fitriani, Darmanto, and Pusdiktasari, 2022);
- Use of GIS information tools for the understanding of COVID-19 patterns (see Kanaujia and Kumar, 2020);
- Design of scorecards and dashboards for tracing critical limits of corona cases (see Nijkamp and Kourtit, 2022);
- Analysis of mobility activities on the geographical spread of COVID-19 (see Bouzouina, Kourtit and Nijkamp, 2022);
- Use of crowd-sourced geo-statistics for the study of cyclists' spatial behavior in corona times (Kourtit *et al.*, 2023);
- Econometric estimation of the interactive effects between COVID-19 and economic growth (see Feng *et al.*, 2022);
- Impact analysis of the occurrence of COVID-19 on human health and well-being (see Grimes, 2022);
- Use of deep learning (AI, ML, CNN) techniques for pattern recognition and causality identification in complex and big data corona systems (see Asiana and Jacob, 2022);
- Econometric analysis of tourists' choices towards deconcentrated and less crowded destinations as a result of the corona crisis (Lim *et al.*, 2022);
- Statistical analysis and GIS of COVID-19 on the leisure behavior of people (see Östh *et al.*, 2023).

This is certainly a rather selective list of topics and approaches, but it clearly highlights the broad range of quantitative spatial corona studies. Consulting Google Scholar leads to the conclusion that corona research – with ten thousand of publications – has become very popular all over the world, while the number of quantitative (coronametric) studies is also on rising edge. Despite the wide interest in corona phenomena, the intriguing question arises whether the whole field of COVID-19 is well covered in a balanced way and whether there are still glaring gaps in coronametric research. To answer this question, the present paper seeks to design a comprehensive research agenda for coronametric research that is able to identify priority areas from a broad quantitative perspective. The instrument used here is a mind map, which is a methodological tool that maps out in a rather intuitive way the entire spectrum or force field of COVID-19, with a view to the identification of knowledge gaps and questions in a strategic research program. This will be presented in Section 3.

3. A mind map for COVID-19

The corona phenomenon with its capricious space-time dynamics is a typical example of a complex phenomenon. Complex systems are characterized by non-linear dynamics, with often unpredictable outcomes caused by chaotic or fractal characteristics in space and time (see e.g., Reggiani and Nijkamp, 2009; Banaszak *et al.*, 2023). Nowadays such complex systems are also often put in the context of 'big data' and 'deep learning'. These approaches emerged already since the end of WWII, with systems science (e.g., von Bertalanffy 1968), cybernetics (e.g., Wiener, 1948), cognitive systems (see e.g., Simon, 1982), self-organizing systems theory (e.g., Prigogine and Stengers, 1984), agent-based modelling (e.g., Schelling, 1960), fractal geometry (e.g., Mandelbrot, 1982), chaos theory (e.g., Lorenz, 1989), network science (e.g., Granovetter, 1973), spatial complexity (e.g., Bettencourt, 2013), econophysics (e.g., Hommes, 2013), big data science (e.g., Hellerstein and Stonebraker, 2015), or spatial fractal structures (e.g., Banaszak *et al.*, 2023).

Two major challenges in all these analytical and computational modelling approaches are: (i) the recognition of insightful linkages in complex systems that are meaningful from a scientific perspective; (ii) the identification of causal patterns among variables in a dynamic system that are testable and appropriate for predictability purposes. These two conditions are the Achilles' heel of current artificial intelligence, machine learning and computational neural network methods. The computer handling capacity for big data systems has hardly any limits, but the key issue is whether outcomes generated by algorithms without a theoretical or methodological framing contribute to our conceptual, theoretical and analytical insights into real-world questions. This also holds for recent attempts to model complex corona phenomena. These quantitative methods are often used to answer the '*what*' questions in empirical research, but for corona research the '*why*' question (related to causality links) is equally important, while for policy purposes also the '*when*' question (related to time patterns) and the '*where*' question (related to geographical spread) are essential.

It is indeed noteworthy that, in the recent past, several quantitative modelling approaches have been developed that serve to replicate and predict the spread of COVID-19. Such approaches often include medical infection and contagion models, complemented with external factors (such as temperature, weather or season). However, the social, economic, contact and geographical factors are often weakly integrated in these models, especially because it is very difficult to take into consideration the heterogeneity among people (age, health, susceptibility, immunity, ethnicity, socioeconomic status, etc.). A variety of models have been developed in the meantime, such as compartmental models, auto-regressive models or convolution models, in addition to machine learning models or computational neural network models. Particularly difficult is the spatial connectivity in the geographical spread patterns, which leads to complex spatial dependence issues in corona trajectories. It seems for the time being that the two most important challenges in corona research, regarding spatial dynamic pattern analysis and recognition and chain causality identification, are not yet covered at all in quantitative socioeconomic research on COVID-19. In order to map out the various research challenges we have set out to design a mind map to put various corona questions in context, with the aim to arrive at an appropriate framing of knowledge questions in this complex field.

As mentioned above, COVID-19 takes place in a complex spatial-temporal context, with many unpredictable and capricious corona curves. In light of the triple-stage constellation described in the previous section, we present here first an arche-typical corona mind map (see Figure 1). The basic idea of this simplified image is that of course in corona times the main public interest is in the occurrence and growth pattern of corona cases (ranging from infections to death tolls), but that from the perspective of health authorities there is a related urgent attention for the capacity of hospitals to accommodate the rising numbers of people suffering from COVID-19 (both regular admissions and intensive care unit admissions). As we know, in many countries the ability of hospitals to respond to the corona crisis was at stake. Consequently, from the perspective of both humans and medical care facilities, reliable and up-to-date information on corona cases and on hospital capacities appears to be critical. And therefore, these two information blocks form the centerpiece of our mind map in Figure 1.

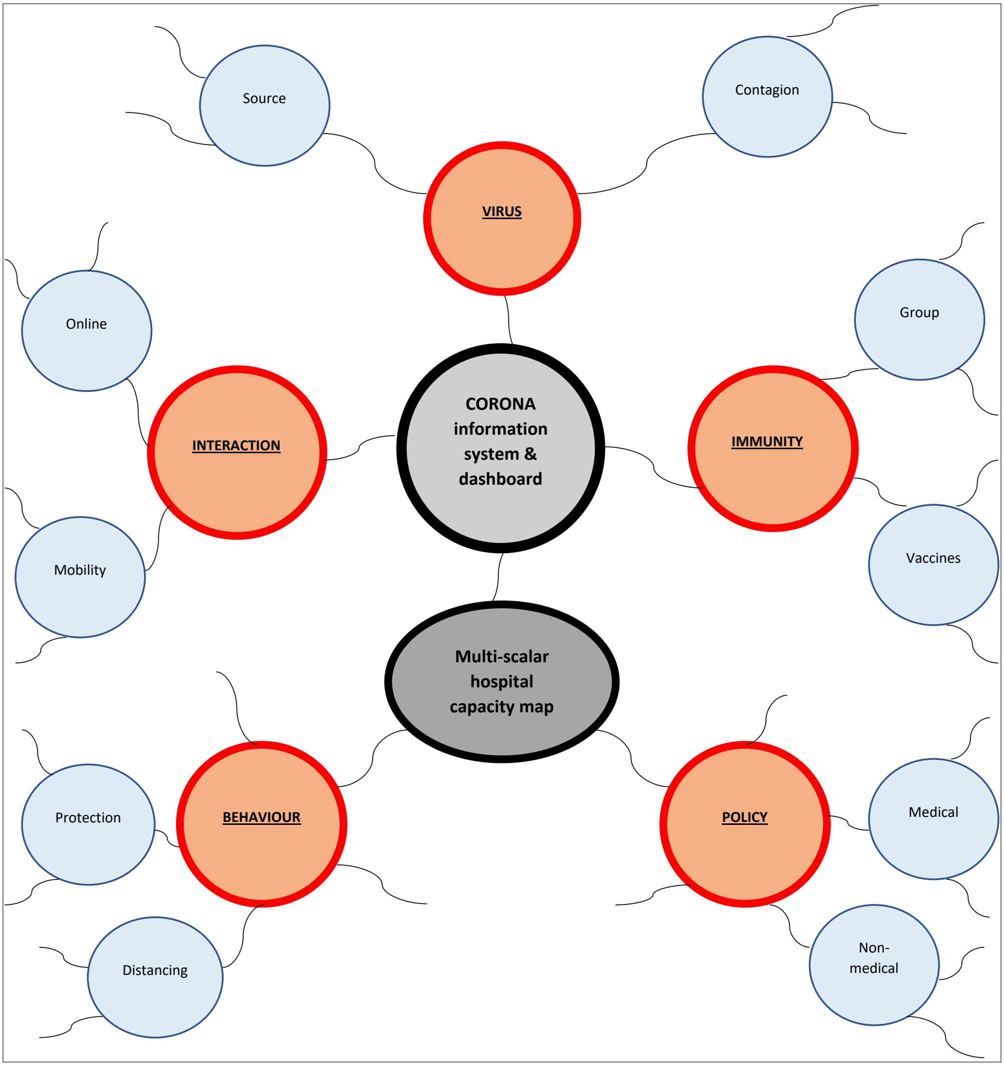

Figure 1: An arche-typical integrative mind map for corona phenomena

We note here that the right upper part of Figure 1 is more oriented to medical-pharmaceutical information, while the left-lower part has more to do with policy and human response behavior. The main building blocks in this arche-typical systemic mind map are the following subsystems: the virus origin subsystem; the virus immunity subsystem; the policy intervention subsystem; the behavioral response subsystem; and the social interaction subsystem.

These five subsystems impact on the two core elements in the center of Figure 1: (i) the corona information system including scorecard data that are contained in the corona dashboard and (ii) medical health care systems of which hospital capacity (beds and personnel) are the critical factors.

It is clear that each of these subsystems can be decomposed into interconnected sub-subsystems, as shown in the illustrative initial mind map of Figure 1. This mind map shapes only the contours of an integrated container image that forms the foundation for an operational data-oriented mind map.

A more extended and operational mind map is depicted in Figure 2, which refers to measurable data and information that is needed to provide an evidence-based map of the complex corona arena. Figure 2 is essentially based on a systematic decomposition methodology as advocated in a recent article by Kourtit (2021). Figure 2 has in essence five main building blocks that altogether represent the complex corona system from a spatial/geographical perspective, with the corona information (in the form of a dashboard) and hospital capacity information as two interconnected pivots in the center of the knowledge arena. We also note that this figure is largely based on the logic of a systems dynamics approach (see Forrester, 1971). The five constituents of this operational mind map will be further presented and discussed in Section 4, followed by a short discussion on long-range corona impacts.

4. Mind map transformation into knowledge domains

The mind maps depicted in Figures 1 and 2 form the main knowledge arenas on the geography of the broad corona phenomenon. However, to distil or generate actionable knowledge more quantitative detail is needed, in particular in regard to geographical scale, time trajectories, statistical comparability, monitoring targets, key performance indicators (KPIs) and normative measurable thresholds. Such more specific information will help establish public trust, community acceptance of policy interventions, and effective management of the complex corona system. All such elements play a role in designing and operationalizing an actionable corona dashboard at an appropriate geographical level. From a spatial data-analytical (gazetteer's) point of view, meaningful requirements for collecting reliable data for useful policy measures based on corona dashboard information are: tailormade space-time data, multiscale design of all available corona information, verifiability and transparency of all data, clear demarcation of regions/cities, attention for geographical differentiation, spatial visualization potential (e.g., digital twins), and interactive user support techniques (e.g., digital viewers). Clearly, the user may represent different roles, e.g. local government (jurisdictional, procedural) or citizen (engagement, empowerment). And therefore, any part of the mind map leading to the design and presentation of appropriate data is also actor-specific and stakeholder-oriented. Against this background, we will now concisely introduce and elaborate the components of the operational mind map as depicted in Figure 2, in the form of a description and interpretation of the underlying interlinked subsystems. For each of these five major subsystems we will briefly discuss the *context* and the *contents*, successively.

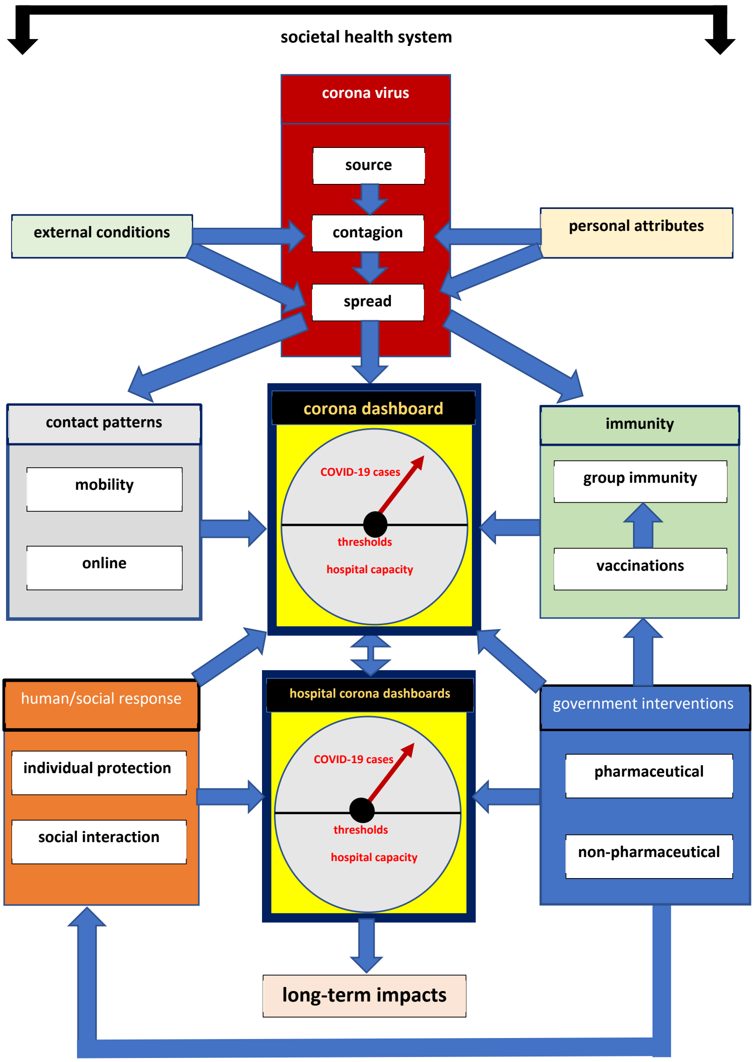

Figure 2: A decomposed operational corona mind map

4.1. The corona virus origin subsystem

Context

The corona virus subsystem is at the heart of the corona genesis (see Figure 3). It addresses the origin of the phenomenon (what, how, when, where etc.) and seeks to collect relevant aggregate and disaggregate data (including space-time dimensions) that might be helpful in monitoring COVID-19, its intertemporal trajectory and its place-specific geographical pattern. This subsystem – and its measurement – is also critical in the identification process of any new contagious disease in the future and its growth pattern.

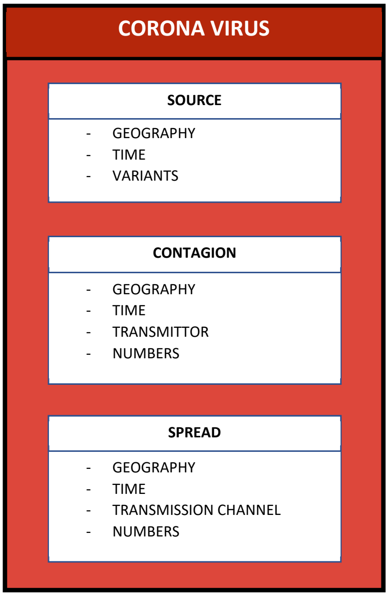

Figure 3: The corona virus subsystem

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The first ingredient of the corona cascade system of Figure 2 is the origin and spread of the virus leading to COVID-19 infections. In this stage a careful inventory and monitoring of the contagious disease, both in space and time, is needed, including the transmission mechanisms. This seems to be a straightforward task, but in reality, the definition of a disease – particularly in case of a decease – is not so easy. For instance, is a person with an already weak immune system or with a terminal disease exclusively dying prematurely due to corona or due to an underlying disease? It is also a fact that in various countries, statistical information on the COVID-19 death toll is approximated by an estimation of the statistical excess number of deaths as compared to the average in a given period over various years. But clearly, this is also a crude estimate, as there may be other intervening factors in the period concerned, while no information is available on the characteristics of people who passed away prematurely. Consequently, there is a need for a clear-cut, consistent and measurable definition of COVID-19 and its subsequent disease pattern, especially in case of a decease.

For a causal understanding of differences in COVID-19 infections, particular attention is needed for two factors, viz. (i) *external conditions* and (ii) *personal attributes of infected people*. External factors comprise *inter alia*: season; weather conditions; environmental quality; population density; transportation/mobility; industrial structure; and job composition. Personal factors refer *inter alia* to: age; health status; vulnerability; physical contact profession; income; education; and culture.

It goes without saying that the collection of all such information in a corona data warehouse is excessively complicated, but ranks high on any corona research agenda.

4.2. The immunity subsystem

Context

Immunity is related to the medical resistance against a health shock or challenge (e.g., a flu). Although immunity is of course an individual health protection feature, in case of an infectious disease the social context is also of decisive importance, while also the impact of vaccinations may be critical (see Figure 4).

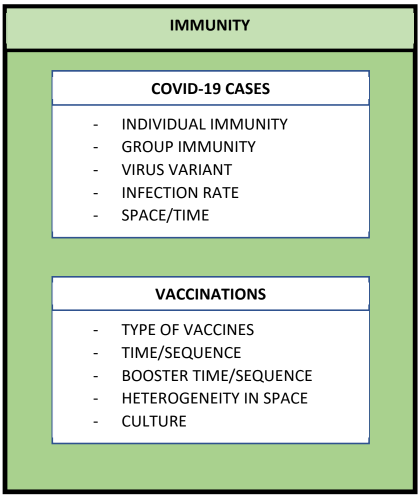

Figure 4: The immunity subsystem

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As mentioned, immunity is an individual feature, that is person– and virus-specifics. Especially in case of many variants of a virus, a complex array of response mechanisms may emerge, both at personal and group level. They all determine the infection rates and survival probabilities, while also the type of vaccines developed to combat a specific virus may have differential effects. In addition, there may be physical and psychological factors involved (including culture and ethnicity) that determine the infection probability and that have altogether an impact on individual and group immunity. A straightforward causality analysis is clearly still fraught with many statistical inference problems.

4.3. The government intervention subsystem

Context

The corona crisis has world-wide been as a major health disaster which called for a smart government policy and sometimes draconic interventions (e.g., Lupu, Maha and Viorică, 2020). Nevertheless, different countries appeared to adopt different policies ranging from strict regulations (e.g., China, New Zealand) to more liberal policy measures (e.g., Sweden). Culture, tradition, geography and trust in governments clearly played an important role (see Figure 5).

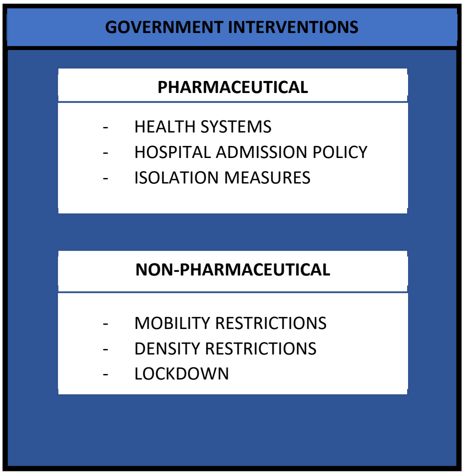

Figure 5: The government intervention subsystem

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A wide range of policy interventions may be distinguished that were implemented in corona times, in particular: (i) pharmaceutical-medical policies (e.g., social distancing, facemasks, hospital intensive care policy, support for vaccination programmes, test stations etc.); (ii) non-medical measures (e.g., closure of public spaces, mobility restrictions, density restrictions, lockdown measures etc.); (iii) financial and economic support systems to keep the economy going. A broad systematic inventory and monitoring of a wide range of such government mechanisms has been undertaken by the Oxford team (see Daly *et al.*, 2020), which has provided a very useful open-access database on corona policy measures.

4.4. The human/social response subsystem

Context

As a contagious disease, the rise and spread of COVID-19 depends critically on the way people respond to a virus. Such a response mechanism appears to be always crucial in the history of infectious diseases. Individual protection measures and group behavior appear to go hand in hand (see Figure 6).

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Individual responses may be manifold, ranging from preventive hygienic measures (like hand washing) or a healthy lifestyle to group behavior (e.g., avoiding close contacts and high densities). Visits to friends and relatives (VFR) and social entertainment appear to be critical factors, but the question is always: how much does it help? Time and again, it appears that a solid, quantifiable and testable causality analysis is still a major problem, especially at individual level.

Figure 6: The human/social response subsystem

4.5. The contact pattern subsystem

Context

The corona crisis has taught us that people are 'social animals'. They like to cluster in groups, and often have a herd behavior. As a consequence, it is very hard to attack the corona virus, as a virus likes to travel through the physical interaction of people (see Figure 7). And clearly, any restriction in free mobility imposed by governments may face fierce resistance. Nevertheless, in many countries people have adjusted their physical contact patterns, voluntarily or compulsory, to the corona health threats.

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Contact patterns are complex phenomena. In the framework of corona policy, not only the contact *per se* is important, but in particular the duration and intensity of contacts, while clearly group size also plays a prominent role. In corona times, many people have also adopted different modes of living and working, such as online shopping, teleworking, distance teaching etc. Clearly, these new digital possibilities have exerted a profound impact on social and socioeconomic behavior of people, and hence on the whole of the corona arena.

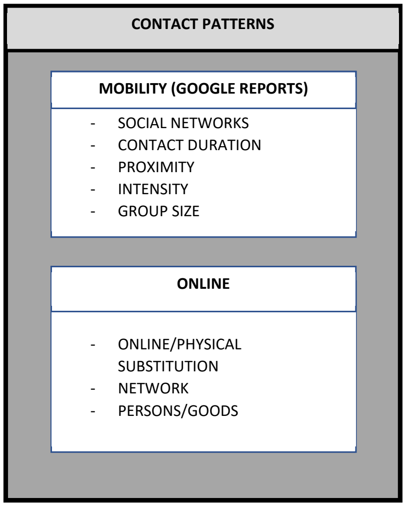


Figure 7: The contact pattern subsystem

4.6. What do we know about long-run impacts?

The corona crisis has undeniably had a far-reaching impact on our societies, with immense human and social costs. Fortunately, the corona virus has been attacked very effectively. But will the corona crisis have a long-lasting effect on our ways of life, e.g., medically, socially, geographically or economically? To arrive at a conclusive answer, much more solid and evidence-based research would be needed on a wide range of knowledge questions. The mind mapping exercise has helped us to identify such knowledge gaps (see Figure 8). Once more, our explorations and observations call for extensive evidence-based space-time causality research, including longitudinal data analysis. But thus far, a comprehensive collaborative corona research programme is sadly missing.

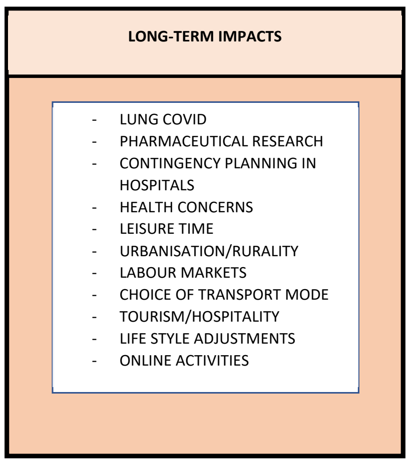
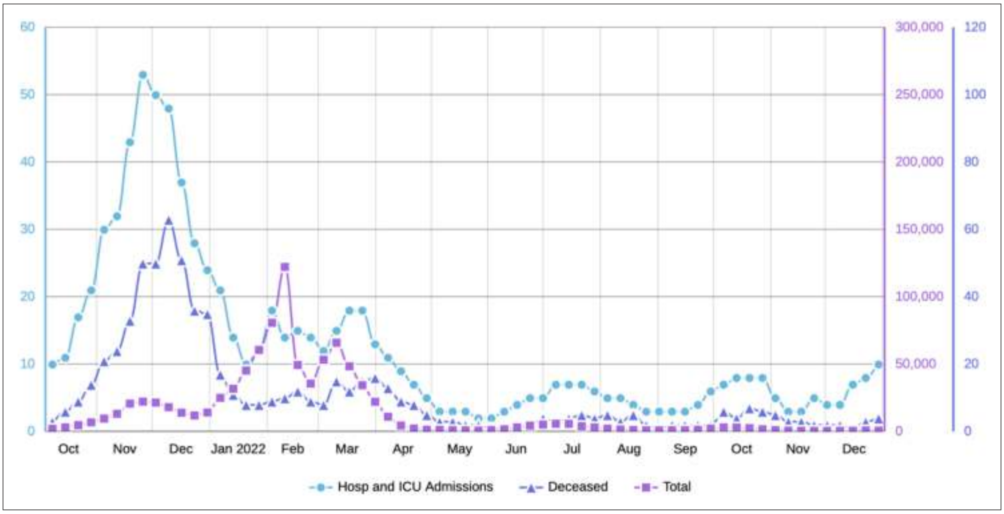


Figure 8: A selection of uncertain long-term impacts

5. An empirical illustration of spatial corona knowledge in the Netherlands

We will now illustrate the potential of empirical corona data. Section 4 of this paper may have given the impression that the corona knowledge base is extremely weak. That is by no means the case; the main problem is the lack of coherent quantitative causality analysis, and hence the lack of predictability of COVID-19 over time, space, groups and individuals. We will illustrate this by presenting in a visual way various relevant data exercises taken from a project in the Netherlands (see for more details Nijkamp and Kourtit, 2022).

The first dataset comprises of the detailed time patterns of corona cases over the Netherlands, including all the successive corona waves, subdivided into COVID-19 infections, hospital admissions and admissions in intensive care units (ICUs), and death tolls (see Figure 9). Such data are not only available at national scale, but also at regional and local scale (see Figure 10 and 11, respectively). This is clearly a comprehensive database. Next, there is also a rich database of the vaccination rates in the Netherlands, as is presented in Figure 12 (in comparison with other countries and continents). Such data are also available at local level in the Netherlands (see Figure 13). Furthermore, for the Netherlands also relevant time series data on the policy stringency index (based on the Oxford study, Daly *et al.*, 2020) are available for the period of explicit government interventions (see Figure 14). And finally, we have also detailed data on interaction and mobility behavior of people, based on Google Mobility Reports, both nationally and locally/regionally (see Figures 15 and 16 respectively). We will now offer a concise interpretation of the various curves mapped out in Figures 9–16.



Note: The vertical axes represent three different scores marked by corresponding colors.

Figure 9: Illustration of corona patterns and curves: cases (December 2022), national level
Source: Authors' own compilation based on CAROU (2022) data.

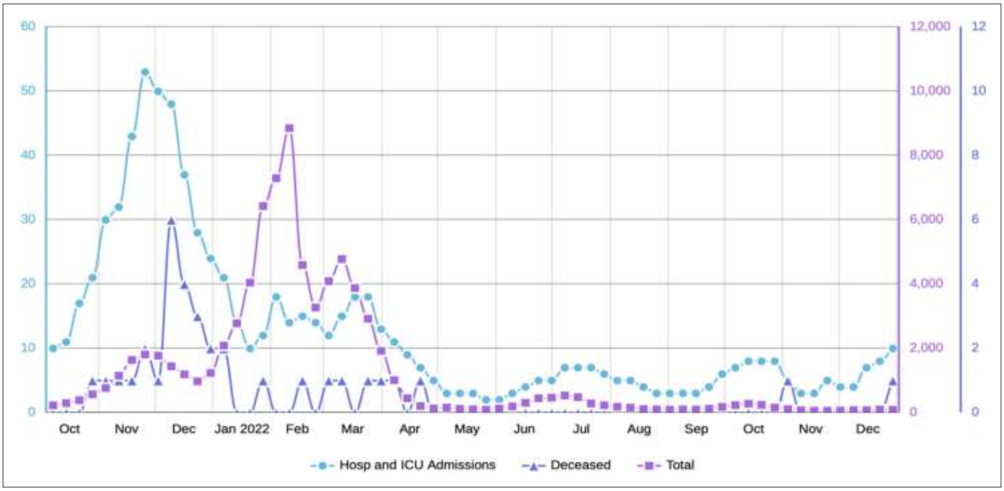


Figure 10: Illustration of corona patterns and curves: cases (December 2022), provincial level (Utrecht)
Source: Authors' own compilation based on CAROU (2022) data.

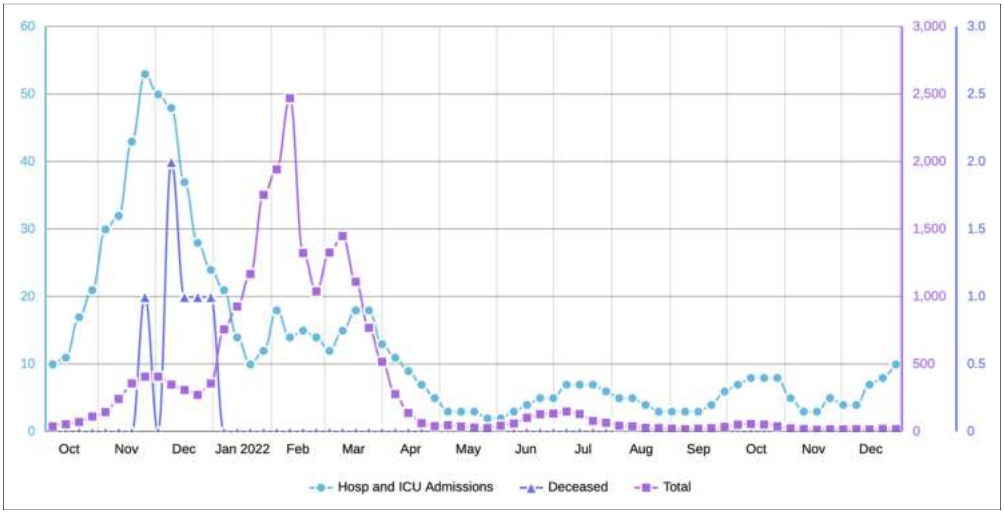
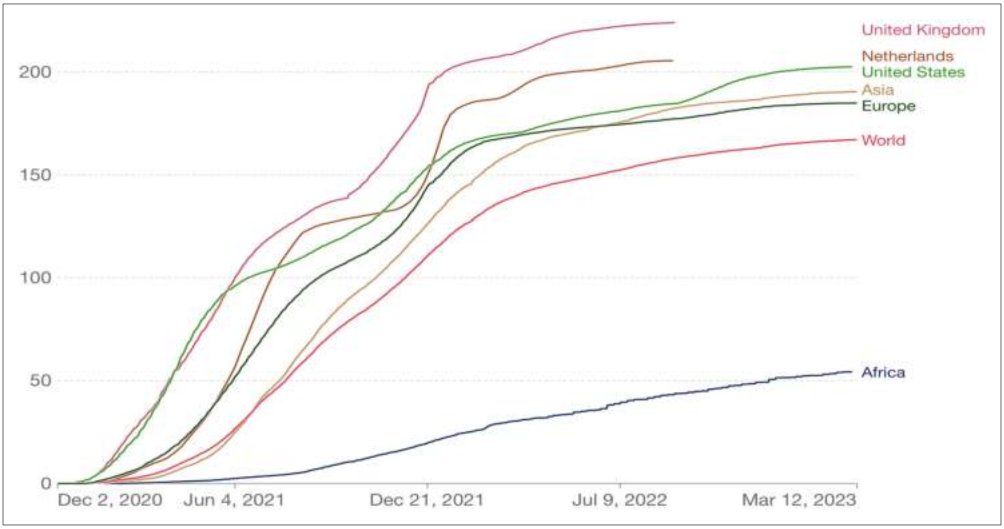


Figure 11: Illustration of corona patterns and curves: cases (December 2022), municipality level (City of Utrecht)
Source: Authors' own compilation based on CAROU (2022) data.

Figure 9 illustrates the short- and intermediate-term patterns of the COVID-19 spreading in the Netherlands, quantified through the number of contaminations, hospital admissions (as well as intensive care admissions) and deaths of COVID-19 patients. The time series of these observed variables illustrate a wave-like relationship that has the form of declining fluctuations at the end of corona times. The various curves appear to be linked to each other, be it with some delay. These data are also available on a regional and municipal level, as is shown in Figures 10 and 11. Here we find again a similar – though not identical – pattern, which suggests quite some heterogeneity in COVID-19 cases depending on the geographical scale.

Figures 12 and 13 describe the time-varying pattern of COVID-19 vaccinations. These figures illustrate that, in the early months of 2021, the vaccination programme in the Netherlands (as well as worldwide) kicked off to some degree, after a slow start the country advanced with high speed its COVID-19 vaccines battle to achieve and safely develop a significant degree of immunity against the serious illness caused by the corona virus. The core idea behind the Dutch vaccination programme was to reach soon a high degree of immunity, as is also displayed in the logistic-shaped vaccine distribution curve. Thus, the aim to significantly increase a broad immunity against the corona virus by reaching a high number of people so as to ensure a high level of protection to cope with the successive waves in order to create and build antibodies against future COVID-19 (re)infections has been rather successful. To understand the complicated policy challenges of managing an array of moderating factors for COVID-19 vaccination acceptance, more attention would be needed for the role of public health policy and reliable communications to the public at large. This holds for both national and local levels of policy.

Figure 14 shows the development of the change and implementation of a wide range of COVID-19 policy interventions for the Netherlands. These data are only available at national level and stem from the Oxford policy stringency index system (Hale *et al*., 2021). These data are subdivided into three categories: pure stringency index, government



Note: For vaccines that require multiple doses, each individual dose is counted. As one and the same person may receive more than one dose, the number of doses per 100 people can be higher than 100.

Figure 12: Illustration of COVID-19 vaccine doses administered per 100 people for The Netherlands compared to the rest of the world (last update March 13, 2023)

Source: Official data collection by Our World in Data (2023).

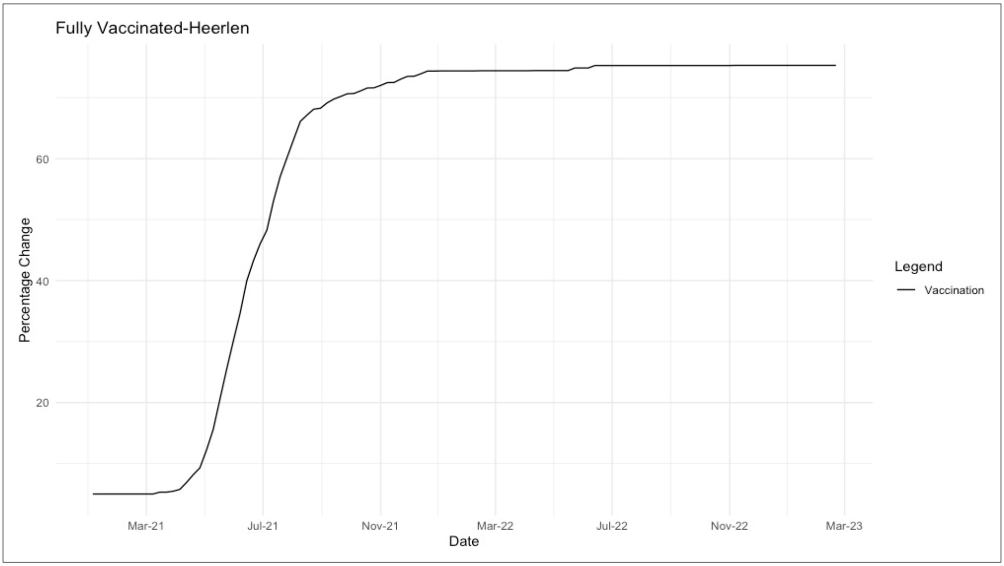


Figure 13: Illustration of COVID-19 fully vaccine doses administered per 100 people for the municipality of Heerlen (last update March 13, 2023).

Source: Data from RIVM (2023).

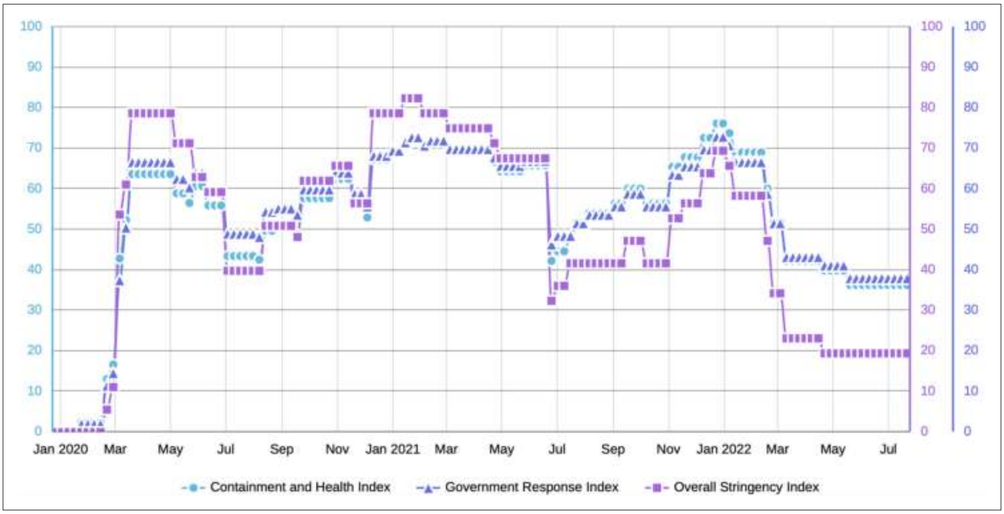


Figure 14: Description of policy stringency curves in The Netherlands
Source: Authors' own compilation based on data from the official data collection by Our World in Data (2022) and RIVM (2022).

response index and containment & health index. Clearly, to manage the corona crisis and reduce the socio-economic impacts of the COVID-19 pandemic through limiting the spread of the disease, next to policy responses, we also need to have information on the spatial interaction (mobility and contact patterns) during corona times.

Figure 15 maps out a variety of spatial interaction/mobility patterns combined with the national policy stringency curve on containing the pandemic. For example, in January 2022, we see partial relaxations of containment measures from the hard lockdown in December 2021, accompanied by an increase in mobility patterns, for instance, staying in parks and walking around. We also note here that data on mobility patterns and trip motives for each day of the week are also available at regional and local level, across different categories of places from the Google Mobility Report Data (see Figure 16).

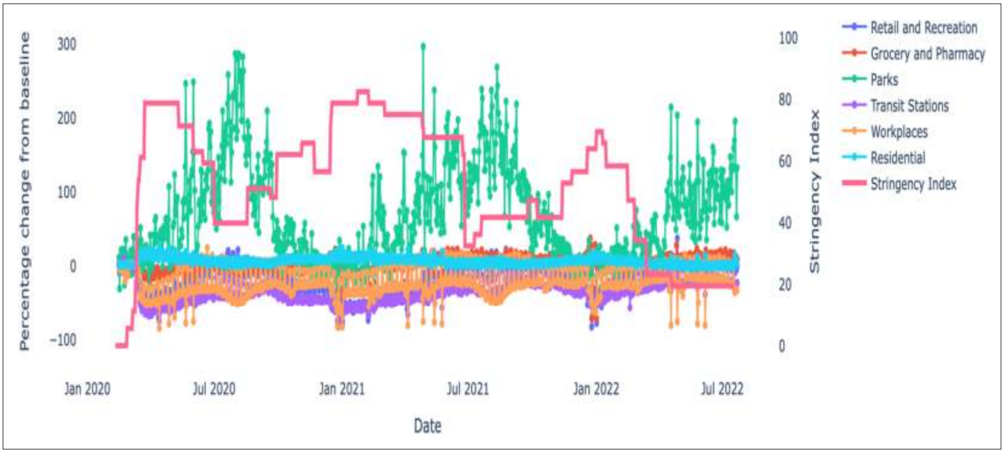


Figure 15: Evolution of mobility patterns (and trip motives) and the aggregate (national) policy stringency index during corona times in The Netherlands.

Source: Data from Google Community Mobility Reports (2022).

Figure 16 visualizes how the daily mobility patterns of people across different categories of trip motives, compared to the baseline days in the Dutch province of Limburg and in the municipality of Heerlen since the onset of the COVID-19 pandemic.

We may thus conclude that a rich database does exist on many elements represented in the mind map of Figure 2, ranging from national to spatially disaggregate scales. However, the main analytical challenge is to identify statistical regularities or preferably causal linkages between the wide diversity of heavily fluctuating curves in the corona space-time arena. These observations prompt in particular the question on the effectiveness and consequences of mobility patterns, government responses, vaccinations and COVID-19 cases in a complex space-time reality. It is thus still a great analytical challenge to identify and predict significant large-scale outbreaks of infectious disease as well as supply-chain disruptions in the hospital sector that can lead to drastic sudden changes in people's medical care systems.

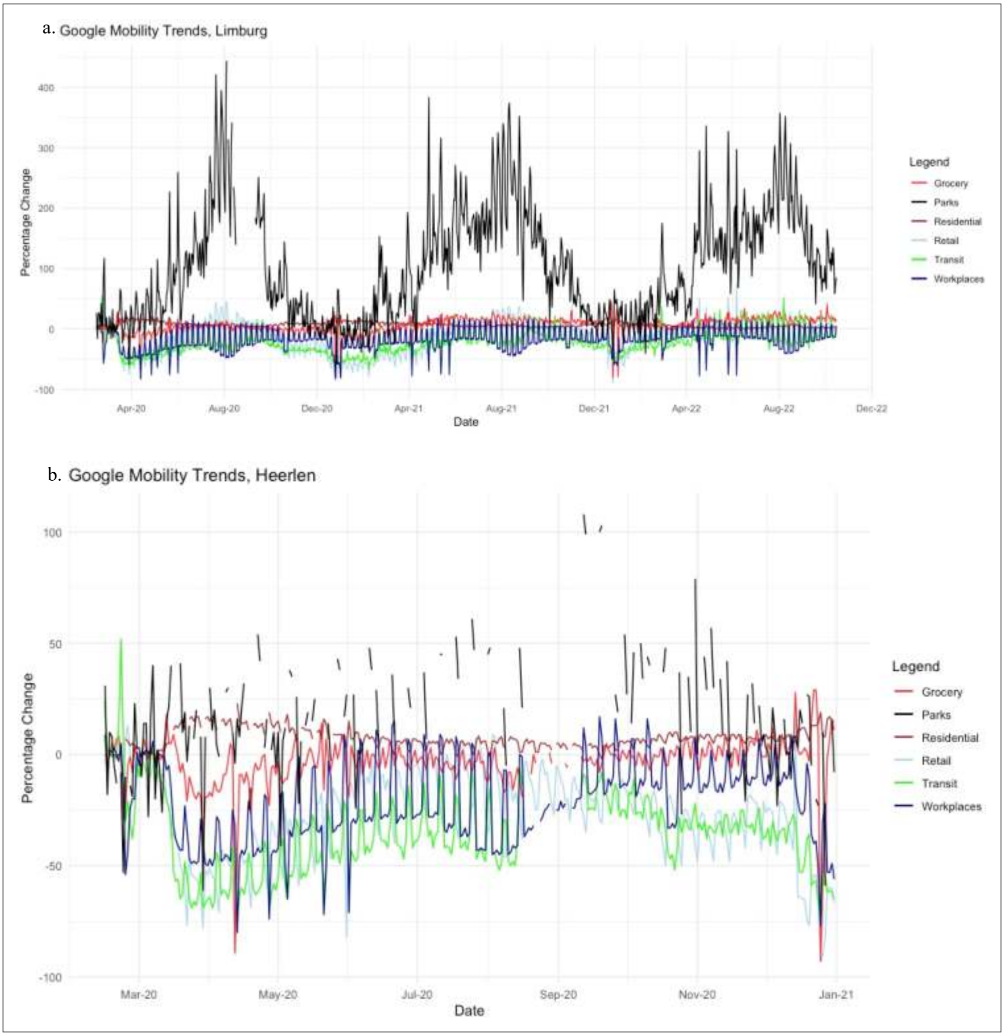


Figure 16: Evolution of mobility patterns (and trip motives) during corona times on regional (Limburg) and municipality level (Heerlen) in The Netherlands

Source: Data from Google Community Mobility Reports (2022).

6. Corona data and Corona knowledge: a 'testimonium paupertatis'?

Corona research has become an overwhelming scientific endeavor, with an abundance of applied scholarly contributions to the literature. Our mind map exercise has tried to design a systematic knowledge architecture for the generation of insightful and actionable insights into the spatial or geographic complexity of this phenomenon. This is particularly important, as space is the medium through which people interact and hence transmit infectious diseases. The avalanche of corona data is indeed amazing, as was clearly illustrated in Section 5. Thus, we have a huge collection of data that are directly or indirectly related to COVID-19. But the space-time dynamics of such data displays a complex interdependent system, which makes it hard to identify unambiguously causal and actionable effects. Simple statistical causality analyses and conventional econometric modelling efforts may at best be useful to trace partial causal links, but do not offer a comprehensive perspective.

Examples of empirical questions that still need thorough attention and research are: the impact of sanitary conditions on the occurrence and severity of COVID-19, the intervening effect of social conditions (e.g., segregation, poverty) on the rise and spread of COVID-19, the possible implications of foodstuff quality and healthy lifestyle for corona contagion, the broader effect of economic structures (e.g., labor markets) on corona vulnerability patterns, and the mitigating effect of various kinds of government interventions on COVID-19 cases or hospital admissions. In addition to data requirements, there is a great need in pandemetrics for explanatory empirical evidence that has also a predictive value.

Clearly, corona dashboards – as depicted in our mind map in Figure 1 or 2 – may be helpful to zoom in on prespecified important corona variables or indicators, but even in such cases the underlying mechanisms shaping the dashboard outcomes are not always clear, and certainly not always convincing from the perspective of predictive power. Consequently, many questions remain, for instance, on clinical crisis planning, on the timely assessment of hospital capacities, on the impact of external factors (e.g., weather conditions, spatial mobility patterns) on COVID-19 cases, on the potential of digital health care services, on the effect of government interventions on dashboard outcomes, on the impact of public dashboard outcomes on human behavior, and many more questions in which causal explanation and predictions are critical. The knowledge agenda for corona research is indeed vast. The data are often available, but the right methodology is usually missing. Fortunately, new advances in deep learning (including AI, ML and CNN) (see e.g., Choudhary *et al.*, 2022) may offer new promising opportunities for pattern recognition in corona research and for causality analysis, once a conceptual, analytical and testable framework (e.g., based on our corona mind map) can be designed that is suitable for empirical testing in a big data environment. It goes without saying that corona research will need much more evidence-based and quantitative research from a social science point of view in order to provide meaningful and actionable support for health care policy in regard to pandemics in the future.

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