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Unveiling a Comprehensive Taxonomy for Data-Driven Decision-Making in Government: Assessing the Use of Data for Covid-19 Responses

Master Thesis

submitted by

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DIGITAL INNOVATION & THE PUBLIC SECTOR

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Abstract

The increasing availability of data changes the way the public sector makes policies and decisions which is discussed in the literature on data-driven government. However, the subject of data-driven decision-making and how to implement these efforts lacks a conceptual overview or guide so far. With this development also comes the question of how data-driven decision-making can be used to inform government and what the relevant drivers and barriers are that should be considered when implanting such efforts. To this extent, this thesis adds to existing research by developing a taxonomy for data-driven decision-making in government based on the approach by Nickerson et al. A taxonomy provides a systematic, structured, and comprehensive conceptual understanding of the topic. This was done through a systematic literature review to assess the existing body of knowledge on the subject. The taxonomy was subsequently evaluated by applying it to three cases, namely the use of data for strategic decision-making for government responses to Covid-19 in Germany, Sweden, and the UK. This confirmed the applicability of the taxonomy but also resulted in an overview of the relevant barriers and drivers to data-driven decision-making in literature and case studies which can guide government decision-makers.

Contents

List of Figures

0.1 List of abbreviations

1. JBC – Joint Biosecurity Centre (UK)
2. DHSC – Department of Health and Social Care (UK)
3. DIVI - German Interdisciplinary Association for Intensive and Emergency Medicine
4. IfSG - Federal Law on the Protection against Infections (Germany)
5. JBC – Joint Biosecurity Centre (UK)
6. KResCo - Krisenmanagement und Resilienz – Corona, Research project by Fraunhofer Institut
7. NHS – National Health Service (UK)
8. ONS – Office for National Statistics (UK)
9. PHA – Public Health Agency (Sweden)
10. PHE – Public Health England (UK public health agency)
11. RKI – Robert Koch Institut (German federal health agency)
12. SAGE - Scientific Board for Emergencies (UK)
13. WHO – World Health Organization

1 Introduction

The technological developments of the past few decades have profoundly changed how government delivers public services and public value. An increasing volume of data enables decision-makers in government institutions to change policy- and decision-making (van Ooijen et al., 2019). Big Data and data analytics can be used to inform decision-making by gathering insights on what should be done and giving a decision-maker an optimal decision based on the available data (Delen & Demirkan, 2013). Decision makers can use tailor-made, case-specific insights and knowledge to act upon (van Ooijen et al., 2019). In that sense, this type of data management and use can be highly valuable in informing decision-making in government (Mahanti, 2022). However, implementing a new technology, such as data anlysis and data analytics is not automatically the answer to any policy problem, but needs sufficient conditions to trigger its problem-solving capabilities (Mora et al., 2021). Hence, it is necessary to be able to conceptualize the use of data-driven decision-making in government and be aware of the potential barriers and drivers of its implementation.

The concept of data-driven decsion-making falls under the theoretical umbrella of a data-driven public sector. By utilizing available information, a data-driven public sector has the potential to enhance policies and provide better services to its citizens. This may be the ability of governments and the public sector to use data to better prepare their country for the future. Here, data can be used for foresight, pattern analysis, and trend analysis to better respond to emerging threats and set up systems and procedures to respond to risks in time (van Ooijen et al., 2019). Arguably,

> (a) Data-Driven Public Sector (DDPS) transforms the design, delivery, and monitoring of public policies and services through the management, sharing, and use of data." (van Ooijen et al., 2019, p. 2).

. A data-driven mode of policy-making then is an extension of traditional decision-making, only that data is used much more frequently and in much larger volumes. This is a development that had accelerated immensely over the past 20 years with the emergence of new technologies, for example, real-time data collection, and data analysis methods, such as predictive, or prescriptive modeling using big data (Dingelstad et al., 2022).

However, the impact of big data on public sector services and on decision-making remain understudied (Kempeneer, 2021). Several researchers call for further research into the use of big data in government and policymaking (Suominen & Hajikhani, 2021), and to include such aspects as the effect of data-driven policymaking on the inclusion of invisible parts of the population (Longo et al., 2017), transparency (Poel et al., 2018), or inclusiveness (Mergel et al., 2019). This issue is not only about having the right information to inform decision-making. A decision-maker may lack the ability, conviction or motivation, political support, or ethics to make a good decision based on data (van Ooijen et al., 2019). Therefore, it is necessary to study the topic of data-driven decision-making in government further and conceptualize it into a usable framework to inform decision-makers, relevant institutions and public administration personnel.

The objective of this thesis is to bridge the research gap by aggregating and synthesizing the existing knowledge on data-driven decision-making in government. This will provide a state-of-the-art picture of the main drivers, definitions, benefits, building blocks, and concepts on this topic, and motivate and facilitate further research in this direction. To this extent, the research is motivated by the research questions:

1. What are the main dimensions and characteristics that define data-driven decision-making?

2. What are the drivers and barriers that should be considered when implementing data-driven decision-making?

3. How could the taxonomy be used to evaluate national data-driven decision-making in government responses to Covid-19?

To answer these questions, the thesis will develop a comprehensive conceptual framework for data-driven decision-making in government through the development of a taxonomy, following the methodological approach by Nickerson et al. for taxonomy development. A systematic literature review will uncover existing categories and building blocks that make up the concept. These are grouped into dimensions and characteristics to build a usable taxonomy for the implementation of data-driven decision-making efforts. This will also indicate the drivers and barriers for each dimension. In line with the method, this taxonomy needs to be evaluated by applying it to real cases. Here, Brandt et al. point to the value of using the Covid-19 pandemic as a case to examine the use of analytics in government decision-making to add to existing research (Brandt et al., 2021). This case is therefore equally useful to evaluate a potential framework for data-driven decision-making.

While basing decisions upon the available data and Big Data were the foundation of every Covid-19 response and research effort, different countries utilized these methods to varying extents for decision-making Mahanti, 2022. By analyzing these cases through the lens of the data-driven decision-making in government taxonmy, it is possible to detect the barriers and opportunities of data-driven decision-making and their relevance for future implementation in the public sector, including pandemic and crisis responses.

The thesis consists of three chapters. The first chapter introduces the methodology and research design. To this extent, it will outline the taxonomy approach by Nickerson et al. and the methodological underpinnings of the building and evaluation of the taxonomy. Additionally, it will discuss the cases that were used for the evaluation and highlight possible limitations of using this methodology. The second chapter is the systematic literature review, which results in the derived framework. The final chapter consists of a case study that applies the framework to three cases of national data-driven decision-making, namely the use of data for decision-making to test its applicability. A final discussion part will assess how the taxonomy performed, and if the barriers and drivers identified in the framework correspond to those of the application cases.

2 Methodology

To achieve the aforementioned research goals, the thesis will employ a design science approach in developing the artifact of a conceptual framework based on a systematic literature review. The goal is to develop a framework for data-driven decision and policymaking that can be used to inform and assess crisis response and be used for further research. Specifically, the research will follow Nickerson, Varshney, and Muntermann's (2017) approach of building and evaluating a taxonomy to show the current state of research on data governance in the public sector and test the found framework against three cases of data governance during Covid-19. The cases used will be three countries' use of data-driven decision-making for their Covid-19 response.

2.1 Taxonomy

As the thesis sets out to develop the concept of data-driven decision-making, a literature review is one of the most commonly used research methodologies as it can present an in-depth analysis of the current academic research on a particular topic or cases (Okoli, 2015). A systematic literature review can ensure that no relevant articles and information are left out and reduce the researcher's bias, which is one of the most prevalent issues with desk research in general (van Thiel, 2021).

While recently there have been numerous updates on the literature review methodology in Information Systems (Okoli, 2015) and Public Management literature (van Thiel, 2014). According to Fink, a systematic literature review can be defined as

> "a systematic, explicit, [comprehensive,] and reproducible method for identifying, evaluating, and synthesizing the existing body of completed and recorded work produced by researchers, scholars, and practitioners" (Fink, 2006, p. 17)

.While there are a variety of literature review approaches (Watson & Webster, 2020). These authors argue that in the IS field review articles are still widely underrepresented, but it is necessary to add more literature reviews to the field to advance theory in the field and promote further IS research (Watson & Webster, 2020). While their article was already published in 2002, this statement was reiterated by more current research (Okoli, 2015) and (Watson & Webster, 2020).

Seeing these arguments, it made sense to follow a systematic approach to developing a framework. Nickerson et al presented the most comprehensive and also most widely used framework for using a literature review. While in past research, different taxonomies have been proposed, they have mostly followed a more ad hoc approach (Nickerson et al., 2017). The approach proposed by Nickerson et al, on the other hand, introduces a systematic method that can be followed to develop comprehensive taxonomies. By doing so it is possible to achieve the goals of this thesis, namely to categorize and conceptualize the current research on data-driven decision-making to identify the building blocks for implementation and identify the drivers and barriers to doing so.

While taxonomy development is a long-used methodology in some disciplines, such as biology and social sciences, there is huge potential and need for this method to systematically assess concepts in IS research (Nickerson et al., 2017), as well as in the disciplines of public administration and public management (van Thiel, 2021). By systematically assessing the existing research and developing a taxonomy, it becomes possible to order complex subjects, such as the topic of data-driven decision-making in the public sector to assist practitioners and future research, as well as potentially lead to new research directions. This is especially useful for the research of more recent topics and emerging technologies and technology applications, such as the use of data for decision-making (Nickerson et al., 2017). Plus, it will answer the research question of what the current, up-to-date state of the research is on government data-driven decision-making in a systematic and reusable way.

A taxonomy here is a robust, concise, extendible, comprehensive, and explanatory classification of dimensions in prior research (Nickerson et al., 2017). By doing this, this paper will be able to develop a new taxonomy in the domain of decision-making based on data and Big Data in the public sector. This is relevant as this topic has shown to be highly relevant in policymaking in the recent crises that governments and the public sector face. Researchers and especially users, such as in government offices or consulting research institutions need to be able to consult existing knowledge and defined concepts to justify and consult (van Thiel, 2014). This taxonomy may provide a basis for doing this and also where the research gaps are and should be filled with new knowledge on the topic. This was an explanatory approach which meant that the goal was not to describe every object in a lot of detail, but rather provide explanations on the chosen topic (Nickerson et al., 2017).

Nickerson's approach originates from the design science paradigm that has the aim to address new knowledge named artifacts, which could be methods, constructs, models, or instantiations (Nickerson et al., 2017). Design science research is done in two research processes, namely artifact building and artifact evaluation (Nickerson et al., 2017). In this way, this paper will first build an artifact, namely the taxonomy of

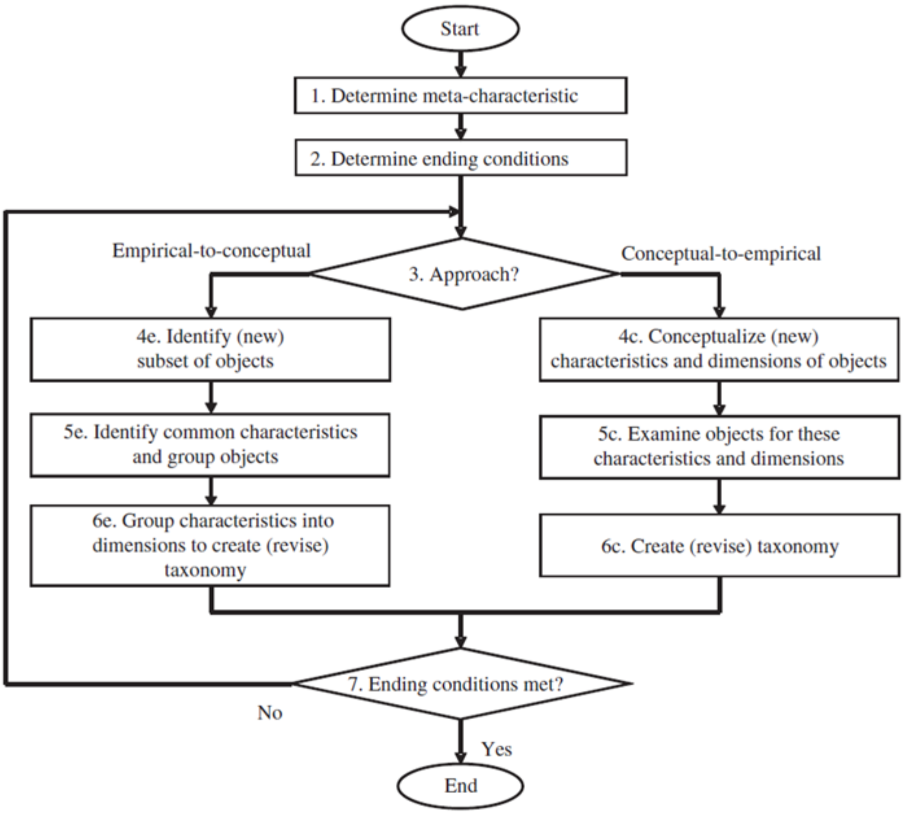

Figure 1 Taxonomy development by Nickerson et al. (2017)

(a) The above model shows Nickerson's approach to developing a taxonomy in IS research.

data-driven decision-making, and in the next step evaluate it by testing it on cases to reveal its efficacy in classifying objects of interest, in this case, the use of data to inform policymaking during Covid-19.

2.2 Artifact development

Here, it was important to respect certain guidelines that Nickerson et al. deem necessary for successfully building the taxonomy. It was essential to take into account alternative approaches during the development of the taxonomy, which reduces the risk of including ad hoc characteristics in the taxonomy. This was done by continuously re-evaluating the themes found in the literature and weighing their importance. Second, the literature considered for building the taxonomy must be from a reasonable timeframe to choose an appropriate scope so it leads to a usable taxonomy (Nickerson et al., 2017). How these aspects were applied in this thesis will be outlined in the following part of the thesis.

The first step according to Nickerson et al. is to identify a meta-characteristic that can be understood as a lens or guideline, as all research is underpinned by some theoretical assumptions in any case. Nickerson et al. state "The meta-characteristic is the most comprehensive characteristic that will serve as the basis for the choice of characteristics in the taxonomy" (2017, p.342). This lens can be the viewpoint of the user of the taxonomy which may guide the researcher in determining the dimensions and characteristics from the literature review (Nickerson et al., 2017). For this thesis, the meta-characteristic was decided to be the implementation of data-driven decision-making, from a governmental point of view.

The second step was to determine an ending condition. Essentially this signifies the state of when to end the iterative process of re-evaluating the literature and when to determine a final dimension or characteristic. Nickerson et al. state fundamental objective ending condition is that the taxonomy must satisfy our definition of a taxonomy, specifically that it consists of dimensions each with mutually exclusive and collectively exhaustive characteristics" (2017, p.343). It is important to determine this beforehand to ensure the development of comprehensive and valid results. Nickerson et al. offer a variety of options as objective ending conditions, for this thesis it was determined to use (1) "every characteristic is unique within its dimension", and (2) "all objects or a representative sample of objects have been examined", and (3) "no new dimensions of characteristic were added in the last iteration" (Nickerson et al., 2017, p. 344).

Step 3 determined the kind of approach, for this thesis the conceptual-to-empirical, as this fits the objective to categorize the literature. Steps 4 through 6 determine the iterative approach of conceptualizing the characteristics and dimensions of the object, then examining the objects for those characteristics and dimensions before creating and revising the taxonomy. Finally, the process ends when the ending conditions are met (Nickerson et al., 2017).

2.2.1 Data collection

The following part explains the data collection for the literature review. As there are many articles and journals concerning themselves with the general topic area of a data-driven public sector in general, it was necessary to narrow down the literature search to focus on the concept of how data impacts decision-making. There are several ways of doing this, but for this paper, it was deemed useful to first, reduce the time frame of the publications, second to focus thematically only on articles that specifically discussed data-driven decision-making or included content on this topic specifically, and finally to only choose articles from representative journals.

In detail, it was deemed useful to only choose to only include high-level journals by researching the publications H-index (Okoli, 2015). Additionally, it made sense to

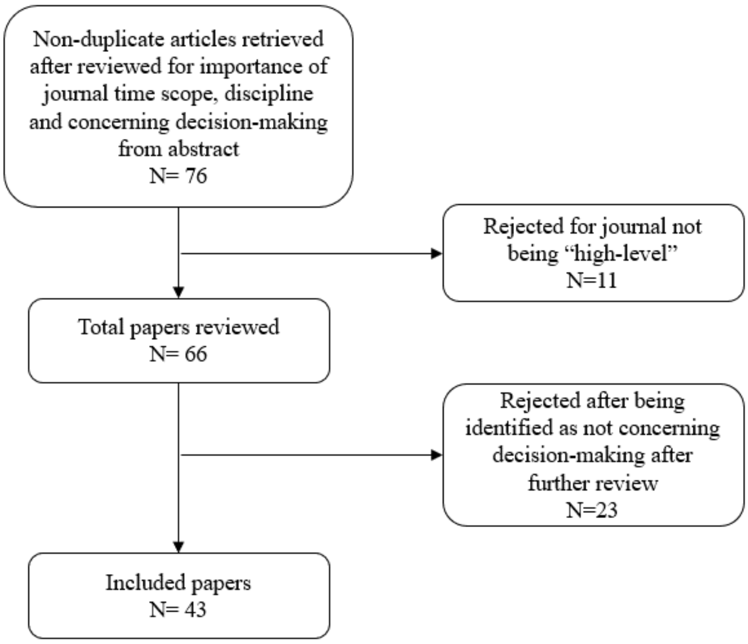

Figure 2 Data collection process (Source: Author)

(a) The above model depicts the process of data collection for the literature review

only consult very recent literature, as the field of information systems and the topics of Big Data, data governance, and analytics as with technology in general, is developing and changing very fast. To ensure up-to-date research and the current state of the academic debate on the topic, therefore the time frame for the search was set to only begin in 2016. As this topic lies at the intersection of IS and Public Administration, these relevant journals were also included. For example, several journals focus on the intersection of Public Administration and IS, such as Government Information Quarterly and Policy and the Internet. Articles from other academic fields, i.e. medicine, education, and so forth, were excluded as well, as they did not implicate policy-making or government decision-making.

Then, several of the most commonly used search engines for academic journals were used to search journals, these being Scopus, Web of Science, and Google Scholar. These portals were searched with the keywords 'data-driven decision-making', 'data-driven policy-making', and 'Data-driven government'. While the search included articles on the broader topic of government use of data, only those articles, where the content specifically related to the use of data for decision-making were included, meaning the results were manually evaluated to ensure the content focused on the narrow scope set out by this thesis. To do so, the articles were scanned to see if their content focus was on public sector and government actions, and narrowly selected for their relation to data-driven policy- or decision-making.

After several iterations of research and article gathering while assessing the aforementioned criteria, plus checking for further references through the bibliographies of said papers, 76 articles were found. After a final round of evaluation and rigorous assessment to ensure the articles exclusively pertained to the use of big data by government or public sector and within this topic pertained to the use of data for decision-making, 43 articles were left to add to the data pool for the literature review.

2.3 Artifact evaluation

According to Nickerson et al., the final step of the taxonomy is to evaluate the derived framework by testing it against real cases (Nickerson et al., 2017). To do this, this paper uses the framework to evaluate three cases of Covid-19 decision-making from three different countries. To achieve this, the data necessary for the case study were assessed through a content analysis guided by the code tree derived from the literature review.

2.3.1 Case selection

To evaluate and test the framework, the thesis will apply the case of data-driven decision-making during Covid-19 pandemic governance. The Covid-19 pandemic presented unprecedented challenges for governments all around the world. Its governance and how to best manage its risks and tribulations of it have been discussed in a wide array of ways in academic literature since 2020. How technology and the digital revolution are highly relevant. Some authors discuss broadly what role technology should play in pandemic decision-making and to what extent technology can facilitate pandemic control and influence decisions in government i.e. (Parra et al., 2021), which opens up the discussion on the use of Big Data and data governance during such a crisis.

With the Covid-19 pandemic, governments have been forced to change their mode of operation to a certain extent: Public authorities had to quickly adjust their decision-making, policy creation, and modification to develop new mandates and emergency response activities to contain the virus and protect their citizens as best as possible (Mahanti, 2022). Countries had to mitigate the risks to human life, but also weigh in on economic losses, and deal with issues such as public trust in government, but also mis- and disinformation (van Ooijen et al., 2019)

According to research, the success of pandemic responses depends on good leadership by governments, well-informed decision-making, existing infrastructures, and available technology (Mahanti, 2022). While there have been plenty of pandemics in history, the availability of useful technology, tools, and resources – data - to inform decision-making has changed. In a digital world, governments can and need to make use of new sources of data to keep their citizens safe in ways that were not possible in past centuries and decades (Mahanti, 2022). Governments need to act on the data they have on the virus spread and the behavior of their citizens. To do so, they need to manage the existing data in a useful way. Therefore, this is a highly relevant case to use to test the framework.

The data that informed decision-making was from electronic health records and administrative reports, but also web-based artificial intelligence (AI) driven analyses (Dron et al., 2022). During a pandemic, an extensive amount of data could be made available to inform governments on how they should be responding or act. Here, Big Data, Data Analytics, Machine Learning, and AI were applied to evaluate or inform the implementation of public health interventions, always with the goal of flattening the epidemiological curve (Payedimarri et al., 2021). This data was, depending on the country, comprised of surveillance data, gathering numbers on how many persons were infected, which was usually gathered at a local level, numbers of deaths from hospitals, and more. Based on this, political decisions were made, for example on travel restrictions, lockdowns of schools or commercial activities, quarantines, or guidelines on social distancing (Dron et al., 2022).

A pandemic arguably presents unique challenges for decision-making, as it presents many uncertainties and risks that will have a direct impact on human and economic well-being. Therefore, in the time since the pandemic began, decision-making during this time has been scrutinized to assess its effectiveness (Huang et al., 2021), or accelerate political learning and institutional reform (Kuhlmann et al., 2021a). All these aspects show why this is an excellent case to assess the framework for data-driven decision-making.

The chosen cases to assess the framework were the data-driven decision-making during Covid-19 in Germany, the UK, and Sweden. These cases were chosen for several reasons: First, these countries all ranked similarly high on the Global Health Security Index, indicating that they have high capabilities to respond effectively to a pandemic and were therefore comparable (Forman & Mossialos, 2021). Further, they have three distinct governmental structures which will affect the decision-making process. Germany represents a continental European federal state with a strong position in its states, the Lander. Sweden is a Nordic type as a decentralized unitary state, strong local governments, and a strong position of government ministries. The UK with its Westminster model of strong parliamentary power is a unitary state with devolved parliamentary assemblies in Scotland, Wales, and Northern Ireland. However, the devolved governments' decisions can always be overridden by the power of the sovereign parliament in London (Kuhlmann & Wollmann, 2019). And last, the researcher is familiar with all three languages, German, English, and Swedish which facilitated the content analysis. Further, these three countries are also very comparable, as the pandemic began essentially at the same time for these countries, but had three distinct approaches to pandemic governance. These three specific countries also presented different Covid-19 strategies, in terms of lockdowns, mitigating measures, and pandemic management. Sweden represents an exceptional case in a global comparison due to its liberal virus management which will test the framework well (Hanson et al., 2021). It also made sense to choose several cases rather than just one, as the use of relevant data during Covid (electronic health records, observational data, epidemiological modeling, and clinical data) was promising but arguably had very different levels of success (Dron et al., 2022).

2.3.2 Data collection

Content analysis works well for exploratory research (van Thiel, 2021). Relevant resources for data according to van Thiel can be amongst others, annual reports, legal papers, policy documents, and publications, but also speeches in parliament or minutes of relevant meetings (van Thiel, 2021). In this case, content analysis will analyze how decisions were made based on data and data analytics during the Covid-19 pandemic, in Germany, Sweden, and the UK, through the lens of the developed data-driven decision-making framework.

For the literature review, the articles had been retrieved from top journals in the field to ensure high quality (Webster & Watson, 2002). To ensure similar high-quality data, for the case study, relevant data for this project comes from reports about the Covid-19 politics of the respective countries that the countries publish themselves, the OECD, the ministries, and working groups specifically put in place to evaluate pandemic management, which gives some indication on how data was used and to what extent and purpose. For Germany, this was published by the RKI and through the BMJ Global Health journal, for the UK, several official portals were accessed, such as the NHS, and the coronavirus website on gov.uk, but also evaluation meetings minutes by parliament. For Sweden, there were fewer primary sources available, especially specifically regarding data governance topics. This was to be expected as the decision-making process differed from other countries and Sweden's Covid-19 management with Sweden's Covid policy ranking as the most lenient country in

Oxford's Government Stringency Index with a score of zero (Pashakhanlou, 2022). However, this was especially useful to test the framework based on limited data and to detect if the framework could hold up. The data that was found came from reports from Folkshalsomyndigheten, the Swedish Public Health Agency (PHA), publications from the Swedish government, and complementing academic reports. For the content analysis, the official documents and policy reports were coded, guided by the developed framework. The results will be outlined in the Artifact Evaluation chapter, before being discussed in the Discussion chapter.

2.4 Limitations

Nickerson's approach has many advantages: It offers the researcher a lot of flexibility in developing the framework and adapting the method to their needs. The artifacts that are developed using this method are likely to be more comprehensive than taxonomies resulting from traditional typologies with an emphasis on ideal types. Plus they are suitable to be extended in further research, thus presenting a good opportunity to keep the research up-to-date in a quickly developing academic field (Nickerson et al., 2017).

Naturally, the chosen research design and method also have limitations. Speaking of flexibility leaving the researcher a lot of room for their own judgment, will also result in higher researcher bias. The conceptualization, order, and allotment of characteristics, while based on a rigorous literature review, and by weighing how much it was discussed in the whole of the literature, is a choice the researcher makes. The iterative process with its ending conditions is narrowly defined, but the ending condition still remains in the conscience of the researcher. The scope for the data collection for the literature review was narrow and since the researcher aimed to define the concept of data-driven decision-making narrowly and categorize its enablers and barriers, only a limited number of articles were chosen for review. Research into further keywords could lead to a wider understanding of the topic in future research. Last, this research aimed to indicate the dimensions that make up data-driven decision-making and present the challenges and enablers of each dimension and how these can be applied to case studies. Naturally, further research into each dimension will give more room for more detailed characterizations, as well, which is recommended for upcoming research.

Data collection	Mureddu et al 2020; van Zoonen 2020; van der Voort 2018; Maciejewski 2017; Giest 2017; Pencheva et al 2018; van Veenstra 2020; Ceron and Negri 2016; Longo et al 2017; Mitrou et al 2021; Vydra and Klievink 2019
Data Quality	Vydra and Klievink 2019; Pencheva et al 2019; Maciejewski 2017; Herschel and Miori 2017; van Zoonen 2020; Mureddu et al 2020; Ceron and Negri 2016; Hoechtl et al 2016
Skills and competences	Malomo and Sena 2017; Giest 2017; Vydra and Klievink; Pencheva et al 2019; Dingelstad et al 2022; van Zoonen 2020; Suominen 2021; Poel 2018; Maciejewski 2017; Mergel 2016; Graham et al 2016
Data Analytics application	Vydra and Klievink 2019; Merhi and Bregu 2020; van Zoonen 2020; Giest 2017; Pencheva et al 2020; van der Voort et al 2019; Longo and Dobell 2018; Daniell et al 2016; Longo et al 2017; de Marchi 2016; van Zoonen 2020; van Veenstra et al 2020; Sivarajah et al. 2020; Hoechtl 2016; Dingelstad et al 2022
Automated and AI decision-making (AI)	Charles et al 2022; Maciejewski; Mitrou et al 2021, Saura et al 2022, Paul 2022, Mureddu et al 2020, van Veenstra 2020, Wanckel 2022;
Data Sharing	Giest 2017; Okuyucu and Yavuz 2020; Desouza and Jacob 2017; Prada and Martinez 2018, Merhi and Bregu 2020, Graham et al 2016, Fischer et al 2019,
Legitimacy	Starke and Lunich 2020; Merhi and Bregu 2020; Pencheva et al 2019; Maciejewski, Desouza; Kempeneer 2021; Herschel and Miori 2017; van Veenstra; Dingelstad et al 2022; Vydra and Klievink 2019; de Marchi; Saura et al 2022; van Zoonen 2020; Herschel and Miori 2017 ; Malomo and Sena 2017
Trust	Ceron and Negri 2016; de Fine Licht 2020; Desouza and Jacob 2017; Taylor 2020; Mitrou et al 2021; Starke and Lunich 2020; Daniell et al. 2016; Pencheva et al 2018; Maciejewski 2017; Vydra and Klievink 2019 ;
Transparency	De Fine Licht 2020; Starke and Lunich 2020; Merhi and Bregu 2020; de Fine Licht 2020; Vila et al 2018; van Zoonen 2020; Kempeneer 2021; Dingelstad et al 2022;
Ethics	Taylor 2020; Paul 2022; van Zoonen 2020; Herschel and Miori 2017;

Figure 3 Distribution of articles per dimension (Source: Author)

(a) This table shows the distribution of articles per dimension of the taxonomy.

3 Literature Review - Artifact development

The following chapter will present the literature review, allotted into the chosen dimensions. The research aimed to give an understanding of the current state of the literature on data-driven decision-making and operationalize the concept. Another aim was to show the enablers and challenges of data-driven decision-making. By defining and conceptualizing the topic through dimensions and characteristics, a framework could be developed that can be used to analyze case studies on data-driven decision-making and aid in the implementation of data-driven decision-making in governments.

3.1 Data collection

The first dimension that could be identified in the requirements perspective is data collection. Data collection is made up of two characteristics, they are data access and availability and the data collection infrastructure.

3.1.1 Data access and availability

The first characteristic of data collection that the literature identifies is data access which concerns the process of identifying the right kind of data to collect and the process of gathering the data. Having access to the right kind of data needed for making a specific decision is essential to make a valuable choice (Mureddu et al., 2020). Naturally, this also depends on the availability of data which is essential to inform decision-making (Mitrou et al., 2021).

Access to the right kind of data is highly important, as it rests on the argument that better data will lead to better decisions made (van der Voort et al., 2019) and (Vydra & Klievink, 2019). This also has something to do with the timeliness and speed of the data access and its provisions (Vydra & Klievink, 2019). This concerns the question if data needs to be available in real-time or if this is not actually relevant. Vydra and Klievink argue that while there is the benefit of real-time data, say a "'data lag' of even a few months is close to insignificant when measuring effects that take years or even decades to materialize, especially if there are other dimensions of quality of the measurement to be considered" (2019, p.4). They further argue that this argument still holds up for such situations where decisions need to be made as soon as possible, for example during a crisis (2019). Here, big data lets the analyst and decision-maker make decisions about a wide array of context points. The availability of large data sets allows governments and authorities to understand the realities of their administration better" (2019).

3.1.2 Infrastructure for collection

Data collection is determined by the infrastructure that provides the data. This refers to the implementation of a set structure of institutions and actors that will produce, analyze and share and provide the data to the decision-makers (Giest, 2017). Relevant factors include IT governance, which also includes the data warehouse (van Zoonen, 2020), IT resources governance, IT resources themselves, internal attitude, external attitude, legal compliance, and general data governance actors (Giest, 2017). The technical infrastructure is highly important, according to (Pencheva et al., 2020, p.38) who argue that "it is also necessary to advance the technical infrastructure used by the government for Big Data management, for example through investment in analytics and warehouse optimization". This is reiterated by Giest, who addresses the potential problems in the existing infrastructure for data governance for decision-making. They argue that weak institutional mechanisms are characterized by siloed (data) structure, where data is stored in different formats and inconsistent recordings and point to the problems this may pose for data sharing (2017), which will be discussed further in the next chapter.

In summary, the dimension of data collection can be characterized by the access to and availability of data. The key challenges and opportunities are that more data does not automatically lead to better decisions. For the infrastructure for collection, there needs to be a cohesive technical infrastructure that may be hindered by a siloed collection structure and different collection formats.

3.2 Data quality

The next dimension is data quality. Data quality is characterized by the accuracy of the data, validity, and reliability, and the representativeness of the chosen data sources. That the quality of the data is relevant to the decision-making process is addressed in most papers that were assessed for the literature review, see (van Zoonen, 2020), (Mureddu et al., 2020), Herschel and Miori, 2017, Ceron and Negri, 2016, (Vydra & Klievink, 2019). The literature review revealed that the most commonly cited themes are accuracy, plus validity and reliability.

3.2.1 Accuracy

The first characteristic of data quality that the literature identified is data accuracy. While not all authors agree on the level of importance the accuracy of the data should play in the decision-making process, several authors point to its general importance for data quality.

Within data quality, accuracy relates to the idea – within the techno-optimist worldview -that big data will provide better information that can facilitate better decisions. Specifically, this would mean that the higher the quality of the information is, and the more accurate the derived information is, the better decisions will be (Höchtl et al., 2016),(Vydra & Klievink, 2019). This heavily relies on the concept that the success of a decision is based purely on the empirical input that informs the decision (Maciejewski, 2017); (Vydra & Klievink, 2019). Accuracy then means that the more accurate the empirical data that informs the decision, the more uncertainty is erased from the decision-making (Vydra & Klievink, 2019), which can be seen by several case studies on fraud reduction. Here, decisions by the German Federal Labour Agency, plus the Irish Tax and Customs Authority based on data resulted in a significant reduction of fraudulent benefits claims and tax evasion (Pencheva et al., 2020).

While the authors point out that quantifying the success of a decision or policy is often quite difficult, they show some perspectives on the matter: Both Maciejewski and Hoechtl et al. argue that accuracy in big data decision-making can be achieved through the expansion of databases, better data visualization, and more in-depth analytics (2017 and 2016). This concludes that accuracy is an important aspect of delivering value from data-driven decision-making.

Other authors see the role of accuracy more critically and argue that data quality is not automatically better because of perceived accuracy Here, they argue that it is important to consider a trade-off between accuracy and privacy. If the argument is that more data results in more accuracy through the analytics, more data has to be collected that could infringe on privacy rights. This will be discussed in detail in the privacy and legitimacy chapter (Vydra & Klievink, 2019). However, Vydra and Klievink argue that this can be reconciled by technological solutions, which could be relying on privacy standards such as k-anonymity or even developing new privacy standards (2019).

3.2.2 Reliability and validity

Vydra and Klievink define reliability as “the trust policymakers have in a specific indicator, which is established by having a good track record of accuracy and relevance for policy questions" (2019, p.4). They do argue that reliability is the most important aspect of data quality.

Several authors agree that reliable data will result in a valid outcome, meaning a valid decision (van Zoonen, 2020), (Vydra & Klievink, 2019). According to van Zoonen, reliability is essential to the decision-making process (2020). She argues that this relates to the old "garbage in – garbage out" adage (p. 6), referring to the fact that if the collected data is faulty, the outcome of the data analysis will be equally as faulty. Therefore, it is essential to prepare the data according to the user or application requirements (Mureddu et al., 2020). This can also not be canceled out by other characteristics being sound, such as having a solid data infrastructure and resulting in an invalid outcome. Reliability in the data can be achieved by using reliable indicators (van Zoonen, 2020).

3.2.3 Representativeness

Another characteristic that is discussed in the literature is the phenomenon that is gaps in the provision of data that will impact decision-making which impacts the representativeness of the data. Herschel and Miori point to the fact that oftentimes decision-makers in the public sector will happily ignore that the data they have is incomplete, biased, or even missing contexts because they have a false sense of confidence in Big Data (2017). This is reiterated by Ceron and Negri who argue that in a Big Data world, "when the information available to policymakers exceeds their capacity to process it, this results in information overload which can damage the decision-making process." (2016, p.134f), which makes them overlook obvious gaps.

To summarize, data quality is defined by three characteristics with their drivers and barriers: First, in terms of accuracy, the expansion of databases, better visualization, and more in-depth analytics may reduce uncertainties in the data. Next, in terms of reliability and validity, one needs to implement reliable indicators and consider that faulty data will result in faulty decisions. Finally, representativeness can be ensured if incomplete data is not ignored, but there is a danger of data gaps and generally false confidence in Big Data.

3.3 Skills and competencies

The next dimension the literature review identified is skills and competencies. It is commonly agreed upon in the literature, that governments are slow to take up technology, definitely slower than industry ((Suominen & Hajikhani, 2021); Poel, 2018). Therefore, it is essential to consider the role of data analytics and Big Data in decision-making according to the skills and competencies available in the decision-making of public agencies and institutions.

3.3.1 Role of decision-makers

Dingelstad et al point to the significant role that human resources play in the use of data for decision-making (2022). For decision-making based on data, the primary source of the data that is being used as a basis for the decision is data analysis for which traditional civil servants' skills, such as intuition and experience from the job play less of a role. They conclude that the set of competencies is very different from that in traditional decision-making (Dingelstad et al., 2022). On the other hand, Maciejewski argues that

"It is worth mentioning that big data do not necessarily cause an information overload for decision-makers. The mechanics of their use are based on passive data that are easily available to decision-makers, according to their specific needs. Most of the information processing work is done by computer and the decision-maker receives an output relevant to the programmed task." (2017, p.122)

Dingelstad et al identified eight key dimensions for needed competencies in public sector data governance, these being critical thinking, teamwork, data literacy, dimension expertise, data analytical skills, innovativeness, the ability to engage stakeholders, and finally political astuteness (Dingelstad et al., 2022). In their study on local government workers, they conclude that "local governments need to invest resources in developing or selecting these competencies among their employees, to exploit the possibilities data offers in a responsible way" (Dingelstad et al 2022, p.458). Mergel and Pencheva et al. argue that public institutions need to invest in big data competencies, but at the same time also institutionalize capacity building (2016 and 2020).

3.3.2 Data literacy

The last important characteristic of the data analytics application is the interpretation of the data. Data can be interpreted in different ways, even if the numbers are the same. There are choices to be made in terms of what indicators to add and what data to use for what goal. These choices on what to measure are influenced by values and data is never value-neutral (Longo et al., 2017), meaning it is a challenging task to interpret data. Pencheva et al. assert that public managers and decision-makers can be misled by data if interpreted incorrectly (2018). The more data that is available, the more choices need to be made by humans. Also, the data at the beginning of the analytics process is often 'noisy', meaning complex to comprehend (Pencheva et al., 2020). More data can also lead to mistaking correlation for causation (Vydra & Klievink, 2019).

In summary, the dimension of data analytics application is driven by the opportunities and challenges of implementing a sound data infrastructure that is necessary for data analysis. Additionally, it can be argued that with solid operational capabilities, better decisions can be made through novel data sources for decision-making in policy analytics and data modeling. Finally, this is all determined by the final interpretation of the data analysis.

3.3.3 Collaboration

Several authors point out that usually in public sector decision-making and data governance, data analytics is outsourced to third-party analytics institutions. This implies new challenges and coordination amongst those stakeholders is necessary. However, seeing the lack of skills and competencies in the public institutions themselves as discussed prior, collaboration can be a very effective way to source the right skills and competencies. In terms of challenges, first, the communication and collaboration between stakeholders are novel for civil servants and public sector officials. Giest argues that

> "The use of big data analytics requires more privatization and contracting out of government activities linked to accessing, combining, and making sense of data as well as collaboration across departments and within communities. This is driven by limited expertise within government to deal with the data and often leads to public officials working with stakeholders that they have no experience with" (2017, p.44).

Another important factor in terms of collaboration is a privacy-transparency tradeoff. Involving third parties in the data analysis means granting third-party access to citizens' data and therefore potentially impeding their privacy. To overcome this Graham et al suggest that legal frameworks and following data privacy guidelines and policies must be strictly adhered to and observed (Graham et al 2016). However, the author implies that collaboration between policymakers and data scientists is essential for actionable decision-making (Giest 2017). Mergel (2016) shows this in detail by stating

> "Big data accumulates quickly and seemingly exponentially; it can quickly overwhelm an analyst. Public managers will need the capability to (1)

> manage and process large accumulations of unstructured, semistructured, and structured data; (2) analyze that data into meaningful insights for public operations; and (3) interpret that data in ways that support evidence-based decision-making. We use the term "capability" here advisedly, as public managers will likely use a mix of staff, contractors, and personal resources to manage, analyze, and interpret large-scale data sets, be they administrative or Internet based." (Mergel et al., 2019, p.933).

To summarize, data-driven decision-making changes the competencies that are necessary to make decisions that change the role of civil servants and public sector decision-makers. Data literacy has become highly important and educating the persons in charge of the decision is essential. To overcome this issue, collaborative public-private partnerships are common practice for data-driven decision-making, which requires examining the partnerships.

3.4 Data analysis application

The next dimension is the data analytics application that is required to prepare, analyze, and utilize the data for decision-making.

3.4.1 Data infrastructure

The first characteristic that the literature review identified is the data infrastructure. Having identified the right data for decision-making, the data needs to be stored in such a way that the retrieval and preparation for analysis are made possible. The way the data is managed thus depends heavily on sound data infrastructure (Giest, 2017), even though, even a sound data infrastructure cannot overcome faults in the data itself (van Zoonen, 2020). Pencheva et al. argue that it is necessary to advance and invest in the technical infrastructure for Big Data management systems, for example in warehouse optimization (Pencheva et al., 2020). Merhi and Bregu point out that the quality and effectiveness of the decision-making are dependent on the infrastructure, stating "a decent IT infrastructure is needed for creating value from data" (Merhi & Bregu, 2020, p.608)

Major problems can arise if data is stored in a siloed data infrastructure (Giest, 2017; van Zoonen, 2020). Referring back to the data sharing concept, using data is only possible if the institutional setup and storage are sound. Here, Giest states that

> "IT silo systems (also called stovepipe systems) describe a system which was developed to reduce complexity and create clear rules of reporting

> and decision-making; however, due to increased collaboration and inter-departmental topics, these have become obstacles in the policymaking process” (Giest 2017, p.373).

In summary, a sound data infrastructure and a well-designed management system are highly necessary to inform data-driven decision-making.

3.4.2 Operational capacity

The next characteristic that could be surmised from the literature is operational capability. By operational capability, the framework refers to the idea that data-driven decision-making is effective in its environment. This could be seen by the speed of decision-making, the effectiveness of the decisions taken and simply speaking, better decisions taken.

Here, researchers also discuss the differences between analytics in the public and private sectors. According to some authors, the adoption of analytics in the public sector does not move at the same pace as it does in the private sector (van Veenstra et al., 2020). In the private sector, it is easy to see the value of analytics, as they are mostly just expressed in financial value. There are different challenges for the Public Sector and different outcomes that need to be achieved, and the value that can be derived from it, as they are also often linked to some politically mandated mission. Also, there are some different challenges: Data sensitivity, Data Privacy and Security, collecting and using the “right” data in the right way, and making beneficial decisions based on them (Sivarajah et al., 2020).

To begin with, Dingelstad argues that generally speaking "it is therefore not surprising that DDDM developers, users, and scholars also hypothesize different, faster, more supported, more precise and cheaper decisions than “traditional” decisions based solely on experience and intuition” (Dingelstad et al., 2022, p. 459). This is a sentiment that is reiterated by Van der Voort (2019), (Höchtl et al., 2016), and Maciejewski as well. She argues that through the expansion of databases and thus more extensive analytics better decision-making will take place. This is based on an understanding of policymaking as a largely empirical decision, and by improving the empirical input the output will be better (2016). Some authors only refer to the overall efficiency gains observed in the private sector gained through data-driven decision-making, which they expect to happen for the public sector as well (Vydra & Klievink, 2019). This results in the concept of policy analytics. Building on the works of Tsoukias et al from 2013, De Marchi et al. coined the term as integrating various analytical methods, such as data mining, statistics, and simulation modeling to inform the decision-making process and policy-making process. De Marchi argues that not analytic information is not always the same and has different requirements exist for using analytics for policymaking (2016). He further states

"The term “policy analytics” refers to the development and application of “skills, methodologies, methods, and technologies, which aim to support relevant stakeholders engaged at any stage of a policy cycle, with the aim of facilitating meaningful and informative hindsight, insight, and foresight” (De Marchi et al., 2016, p.28).

Mureddu explains the significance of the modeling and the difference in data modeling. They argue that is a challenge to identify and validate suitable data modeling schemes to deal with the complexity of the available data (2020).

Policy analytics is a modified version of traditional policy analysis, in which the discrete stages of a policy cycle are understood as a continuous, real-time system of collecting big data. This data is provided through new sources of data, that are ubiquitous and interconnected technologies, such as the Internet of Things, mobile smartphones, or electronic payment cards (Longo et al., 2017). By doing this, decision-makers are enabled to define the problems more precisely and understand the policy better through experimentation and insights through continuous assessment of the collected data(Longo & Dobell, 2018). Daniell et al. argue that policy analytics have the potential to enhance decision-making in innovative ways by analyzing and designing policies (Daniell et al., 2016).

The advantage and hopes for the concept of policy analytics is that it would inform more efficient decision-making. However, there are several risks and barriers, including a privacy trade-off, which will be discussed in detail in the following chapter, technical accuracy, or bias in democratic decision-making (Longo and Dobell., 2018). Therefore, these factors need to be observed and taken into account to harness the value of policy analytics.

3.4.3 Interpretation

The last important characteristic of the data analytics application is the interpretation of the data. Data can be interpreted in different ways, even if the numbers are the same. There are choices to be made in terms of what indicators to add and what data to use for what goal. These choices on what to measure are influenced by values and data is never value-neutral (Longo et al., 2017), meaning it is a challenging task to interpret data. Pencheva et al. assert that public managers and decision-makers can be misled by data if interpreted incorrectly (2020). The more data that is available, the more choices need to be made by humans. Also, the data at the beginning of the analytics process is often 'noisy', meaning complex to comprehend (Pencheva et al., 2020). More data can also lead to mistaking correlation for causation (Vydra & Klievink, 2019).

In summary, the dimension of data analytics application is driven by the opportunities and challenges of implementing a sound data infrastructure that is necessary for data analysis. Additionally, it can be argued that with solid operational capabilities, better decisions can be made through novel data sources for decision-making in policy analytics and data modeling. Finally, this is all determined by the final interpretation of the data analysis.

3.5 Automated and AI decision-making

Automated and Artificial Intelligence (AI) decision-making systems are being used increasingly by governments and public sector institutions and must therefore be included in the discussion on data-driven decision-making systems (Mitrou et al., 2021).

3.5.1 Types of decisions

Many decisions nowadays, in the private but also public sector are automated and performed by algorithms (Mureddu et al., 2020). The role of the decision-maker is changing, and a decision does not have to be exclusively made by a human actor anymore. There may be fully automated decisions, humans in-the-loop decisions, or AI may be used in a recommender system, which informs humans on the possible outcomes and decisions but the human decision can still deviate from the recommendation (Mitrou et al., 2021). Other systems are Big Data Algorithmic Systems (BDAS), running on machine learning and other types of AI (Wanckel, 2022).

Mitrou et al say that "AI-supported systems are proposed to be used to automate the decision-making processes (or parts/components thereof) that rely "on clear, fixed and finite criteria" a detailed legal regime that demands no executive discretion" (2021, p.12). In this way, automated decision-making works for routinized, high-frequency decisions that are simple. There is some criticism from scholars, arguing that "such decision support systems may hide discretionary activities and power, revealing possible lacks with regard to oversight of the administrative action" (Mitrou et al 2021, p.12). This also implies that automated decisions are less suitable for more complex decisions that involve still unstructured information, even though AI is still improving and increasing in capacity (Mitrou et al., 2021).

3.5.2 Role of humans

One theme in the literature is the role of humans, civil servants, and decision-makers alike in automated decision systems. Mitrou et al. argue that there still needs to be some degree of human supervision or possibility for human intervention when it comes to AI-assisted decision-making systems (2021). So far, there are fewer use cases of automated decision systems, but rather the literature discusses AI applications in general (Mitrou et al., 2021). In this way, this dimension will be of high relevance for future cases of data-driven decision-making. Generally speaking, when using AI there will be risks that need to be observed and mitigated. If the applications of AI are closely observed and attended by humans, many decisions can become much more efficient (Saura et al., 2022). The literature review identified several risks and guidelines on how AI needs to be managed for data-driven decision-making. Charles et all found risks that the grouped into six categories: "technological, data, and analytical risks and guidelines, informational and communicational risks and guidelines, economic risks and guidelines, social risks and guidelines, and ethical risks and guidelines" (Charles et al., 2022). Several cases of automated decision-making in the public sector that were highly publicized, for example, the Dutch welfare fraud detection system or the Australian robodebt scheme (Paul, 2022, p.498). However, the characteristic of risk will be discussed in the ethics dimension.

3.5.3 Bias

Mitrou et al. discuss the role of public servants in data-driven decision-making processes (2021) and thus the role of their biases in the decision-making process, from the choice of data to the development of algorithms to inform the decisions taken. Bias is seen as a major challenge for automated decision-making and will influence the outcomes of the decision. Van Veenstra et al. explain that bias may originate in the training data that is used to develop and refine algorithms which will eventually affect decision-making (2020).

To summarize, several authors emphasize that not every decision can be made with the help of AI. There is still the need for human control and supervision in automated decision-making. Plus, the risks and the possibility of bias needs to be taken into account when it comes to employing automated decision-making and AI. Generally speaking, the role of AI in decision-making is widely discussed in the literature, however, it is emphasized that there are few used-cases in public administrations at this moment in time, it will however become more and more relevant and should be included in a representative framework on data-driven decision-making.

3.6 Data sharing

The next dimension is data sharing. As it has become clear in the prior section, collaboration between different stakeholders is essential to data-driven decision-making. This of course also includes working across different institutions that are part of the decision, providing data and contextual knowledge, and so forth. Therefore, the relevant data needs to be shared efficiently and without gaps or inconsistencies between departments and institutions to reach the decision-maker and provide the right data to make the right decisions.

3.6.1 Interoperability

The literature review identified that doing so also comes with its own challenges. First, an essential factor is the need to ensure interoperability. Interoperability means that data is stored in such a way that it can be used in different systems and so on seamlessly. Giest argues that digitization has "led to data format inconsistencies where data is stored in diverse ways and formats and data on drugs, staff or locations are recorded differently (Giest, 2017). Naturally, this means that this makes sharing data more difficult and drawing conclusions from the data even more difficult. However, if data Is shared it has many advantages as departments can benefit from wider datasets (Okuyucu & Yavuz, 2020).

Sharing data across institutions can also become complex in regards to preserving citizens' privacy. Rules and regulations need to be in place to ensure the safe and secure sharing of data across departments and institutional borders (Giest, 2017). In her research, Giest encountered the problem that oftentimes there is a siloed data structure in governmental institutions, where the actors explain away not being able to share data by referring to privacy laws. However, she argues that more often than not the real reason is the institutional setup and an archived way of sharing and collecting data (Giest, 2017). While a siloed infrastructure is a common complaint in public management research, digitalisation and IT have added another layer of complexity to the matter (Desouza & Jacob, 2017).

Additionally, sharing data is time-consuming and inefficient in many public sector dimensions, which makes it hard to reach meaningful conclusions in a time-efficient manner even though it is acknowledged that data sharing leads to better decisions and better outcomes for all stakeholders involved (Giest, 2017). On the other hand, it can be argued that the development of data-driven decision-making incentivises institutions to share more of their data on federal, national and regional level (Prada & Martinez, 2018).

3.6.2 Stakeholders

The other big challenge and obstacle in the data sharing dimension is if organizations do not share data. Resistance to sharing one's data and conclusions is a common problem. There must be incentives for all stakeholders that are part of the data-provision and decision-making process to share their data with each other. If they do not do so, it will be impossible to draw comprehensive conclusions (Merhi and Bregu, 2020). The resistance can be attributed to a set of legal, including privacy laws, administrative obstacles, including different infrastructures (Graham et al., 2016), or unclarity about what departments are financially responsible for what (Fischer & Richter, 2019), (Desouza et al., 2017).

In summary, the drivers and barriers of the data-sharing dimension concern the opportunity for wider datasets, the difficulties regarding having interoperable systems, and the role of the stakeholders that need to cooperate.

3.7 Legitimacy

The next dimension is the legitimacy of the decisions taken. The literature shows that the decision-making stakeholders need to be held accountable for their decisions to be perceived as legitimate. Therefore, it is necessary to identify and observe the institutional and legal context that underpins the stakeholders involved in the data provision, collection, sharing,, and generally, the decision-making.

3.7.1 Institutional context

Merhi and Bregu state that in data-driven decision-making, a flexible and dynamic institutional environment is key to success (Merhi and Bregu, 2020). Often data-driven policymaking is done in public-private partnerships which need to be considered (van Zoonen, 2020). The literature shows that the decision-making stakeholders need to be held accountable for their decisions to be perceived as legitimate. Therefore, it is necessary to identify and observe what stakeholders are involved in the data provision, collection, sharing, and generally, the decision-making. Starke and Lunich point to the fact that legitimacy is created through the different stakeholders involved in the data provision and decision-making processes and their institutional and political mandate to do so (Starke & Luenich, 2020). Therefore, it is necessary to discuss the stakeholders, those that affect or are affected by the achievement of the institution's objectives, in the case of data-driven decision-making usually the government, government collaborators, but also the citizens (Dingelstad et al, 2022). Starke and Lunich state that with all technological interventions, data-driven solutions depend on the stakeholder's participation or acceptance (2020). Often, data analytics as a tool for improving decision-making is undervalued in institutions and not recognized for its potential which hinders the process (Pencheva et al., 2020). However, support from senior decision-makers is critical for successful data-driven decision-making (Malomo & Sena, 2017).

Authors distinguish between perceived legitimacy, which encompasses the public perception of legitimacy, and political legitimacy. Kempeneer argues that it is "important that policy makers, along with other stakeholders, establish clear practical and legal guidelines regarding the validity of data-driven knowledge claims" (2021).

There was also a debate in the literature asking if automated decision-making would increase or decrease legitimacy. Perceived legitimacy is arguably lower with automated decision-making as people generally do not understand the underlying technology. Political legitimacy may be higher with automated decision-making as Starke and Lunich argues: "In particular, artificial intelligence (AI) systems have the potential to increase political legitimacy by identifying pressing societal issues, forecasting potential policy outcomes, and evaluating policy effectiveness" (Starke & Luenich, 2020, p.4).

3.7.2 Legal context

For the legal aspect, two important points are to be made: Ensuring a clear democratic mandate, which in turn will also avoid a so-called institutional void, and ensuring compliance with existing data privacy regulations. Any decision made by the government is subject to legality and must be made within the laws of the country. Legal mandates for data collection, data analytics, and data sharing are necessary to assure legitimacy. Administrative authorities are generally controlled by the judiciary in the country when the limits of the mandate are exceeded (Mitrou et al., 2020). Clear legal guidelines are key to ensuring legitimacy in data-driven knowledge claims and decisions (Kempeneer, 2021).

3.7.3 Data Privacy

Authors argue that when it comes to using big data in government, privacy is one of the biggest challenges decision-makers have to address and one of the biggest risks, see (Merhi & Bregu, 2020), (Herschel & Miori, 2017), (Vydra & Klievink, 2019). Merhi and Bregu point towards countries like the US to show the necessity of having a solid and extensive legal framework to ensure data privacy when employing big data analytics, even though naturally this also slows down the process and costs more money

(Merhi & Bregu, 2020). Having a solid data privacy framework in place is necessary to ensure a democratic mandate (van Zoonen, 2020). In the European Union, this is often discussed in terms of the EU General Data Protection Regulation (GDPR). The risks that could arise are that government take surveillance and state control a step too far in collecting and analyzing data about their citizens (van Zoonen, 2020), and exploit their citizen's data (Herschel & Miori, 2017).

Vydra and Klievink address this topic as a trade-off between privacy and empirical validity of the data analysis: To avoid privacy violations, data needs to be distorted, for example through a concept called k-anonymity that makes it possible to not distinguish two individual records which would be in the scope of keeping every citizens' privacy. However, this is shown to make data almost unusable as it will not serve enough data points or content anymore, and also introduces bias (Vydra & Klievink, 2019).

This is also relevant to automated decision-making, as letting an automated system make decisions can endanger a person's privacy rights. Saura et al. argue that the risks, especially in a state of alarm such as an economic or health crisis, user privacy violations increase significantly (Saura et al., 2022). While the removal of personal identifiers from the data records can be a solution to exploiting citizens' privacy and still being able to use the data efficiently, often systems that are being used to analyze the data are automated analytic algorithms that are insensitive to such requirements. However, even the humans who are tasked with data analysis are often overwhelmed by the volume of data and are unable to take further steps to ensure data privacy (Herschel & Miori, 2017).

In summary, legitimacy in the literature on data-driven decision-making can be characterized by the institutional context, which is driven by a clear institutional mandate for all stakeholders that are involved in the data-driven decision-making process from data collection until final decision-makers. Also, the legal and policy frameworks that underpin data governance for decision-making are essential to ensuring legitimate decision-making. This also touches on the aspect of data privacy and protection, where decision-makers need to consider any data privacy trade-offs and protect their citizen's data.

3.8 Trust

The next characteristic the literature review has uncovered is trust. Trust can be characterized by public support and the extent of politicization of the data and evidence.

3.8.1 Public perception

In traditional decision-making, the information for policymaking usually comes from policy experts or agenda-setters. This meant that this information does not necessarily represent the will of the people. In data-driven decision-making, however, prediction markets and sentiment analysis can be used to determine if the people support certain policies or decisions and ensure that the decisions and policies are being supported (Starke & Luenich, 2020), (Taylor, 2020). While public support does not automatically make a policy a good policy, oftentimes public support determines compliance with regulations, for example in crises. Another aspect to consider is where the sentiment data is coming from, if it is gathered from Social media, for example, it might not represent the entirety of the population because of the digital divide (Desouza & Jacob, 2017).

Another aspect is the trust in the quantification of the truth (Taylor 2020). Studies show that people trust machines more to objectively assess data than human non-experts, but still trust human experts the most (Mitrou et al., 2021), or that human skills are perceived as more trustworthy than algorithms (Starke & Luenich, 2020) and (Ceron and Negri, 2016). Citizen participation is also important to discuss as an indicator of public support. Merhi and Regu state that governments can benefit from the use of big data in such as that they can better engage with the public. For example, governments can integrate public opinion data in different stages of the policy cycle (Daniell et al., 2016). This could also mean including those that traditionally are not involved in policymaking can provide feedback o decision-making by governments assessing the preferences of citizens (Pencheva et al., 2020) and let governments draw better conclusions from citizens' feedback to the decisions (Maciejewski, 2017).

Politicization also plays a big role in the attribute of trust. The literature showed that information and decisions based on the information are subject to politicization. Authors argue that decision-making rarely reflects reality (Daniell et al., 2016), but rather reflects the political values that underpin the aims of the decision-maker (de Fine Licht & de Fine Licht, 2020). Data is not neutral and can be used in different ways, and data analysis is underpinned by specific criteria, that reflect political values, and queries that a person will dictate. Therefore, there is an underlying aim that the data can fulfill (Vydra & Klievink, 2019). The choice, selection, and aggregation of data are a value-based process that is often not transparent, and the algorithms that are used for the analysis reflect specific models of social phenomena, factors of importance, perceived correlations, and assumptions (Vydra & Klievink, 2019). In all these ways, data, big data, and data analysis can be used to solidify political arguments and be used to achieve political gain, such as public support for a decision.

Arguably, data-driven decision-making is in fact, based on political choices and thus this aspect must be part of any discussion on the public value of data-driven decision-making.

In summary, trust in data-driven decision-making can be characterized by the attributes of public perception, which brings about the opportunity that data-driven decision-making can be more empirical and less attitude driven than traditional policymaking, and public support can be more easily quantified. However, there is also the challenge surrounding the politicization of the data that underpin the decision-making, which can be used for politicians' gain and preexisting agendas.

3.9 Transparency

The next key theme that could be identified in the literature is transparency. This relates to the openness the governing body provides in the way they use and utilize citizens' data. This aspect closely relates to the dimensions of legitimacy, and ethics but especially trust. However, it is highlighted in the literature to such an extent that it merits its own discussion.

3.9.1 Reporting

To define transparency in the context of the government of data and Big Data, De Fine Licht propose that transparency is key to fostering the public's confidence in decision-making and that transparency will be the core feature (2020). Merhi and Bregu (2020, p. 612) argue that transparency "refers to the extent to which government makes data and information about internal decision processes and procedures available to the public." Merhi and Bregu (2020) point out that generally, governments keep the data that are used for decision-making, hidden from the public. This can make the public suspicious of the data that is being collected, for example in terms of data privacy or protection (de Fine Licht & de Fine Licht, 2020).

3.9.2 Open Data

They also highlight that transparency can also be understood as a significant factor in bringing government and citizens closer together. Explaining and showing the public how government arrives at a decision and policy, will enhance the trust and support that the public has in a certain decision (Merhi & Bregu, 2020). This shows that transparency is very closely related to the dimension of trust, as described in the prior chapter. Now in the digital age, the right to access government data and understand what data is being collected for what purposes is commonly understood as an essential factor of democracy (Merhi & Bregu, 2020). To show the results they can publish data, for example through the use of dashboards, reports, or even open data, which enables governments to share data with their citizens to improve transparency (Merhi & Bregu, 2020).

To present open data, often dashboards as visualization tools have the potential to increase transparency as they are easily understood by different citizen groups (Vila et al., 2018), and they can be continuously updated and kept on websites for both citizens and journalists to stay up to date on the current data. Additionally, they often offer the function of viewing different categories and perspectives as the viewer desires (van Zoonen, 2020). They also present challenges insofar as they also need to have high data quality, accuracy, timely updates, and be compliant with privacy laws, but also to make them representative and look appealing (Vila et al., 2018).

3.9.3 Timing and extent of transparency

Another point is that it is commonly understood that the non-understanding of the underlying technology of data science, AI, and decision-support systems greatly diminishes the trust of the citizens (Starke & Luenich, 2020). Therefore, to guarantee public value, government data used for decision-making must be transparent. De Fine Licht considers the factor of transparency in the decision-making cycle in government, assessing at which point, and to what degree transparency will be the most valuable, specifically in terms of automated decision-making. Is full transparency throughout the entire policy cycle most useful or are there specific points in time where the decision-making process should become open to the public? They argue for a justifications approach of data-driven decision-making, where the government is transparent in the rationale phase of the decision-making, meaning that the citizens will know which actors are providing the data, and which entities are making the decisions and therefore know who they can hold accountable for the decisions that are made, which in turn enhances trust in the decision (de Fine Licht & de Fine Licht, 2020).

They also consider if the people involved in the decision-making process know that they could be monitored by the public, they will act with a sense of responsibility and care. The common assumption may be that public scrutiny "makes decision-makers aware of the public eye, thereby making them aware of their responsibility to work toward the public good rather than in their self-interests" (2020, p.920). This also includes the technological process, where programmers will feel this sense of responsibility in the choice of data, classifiers, and development of the code when they know that their process may become public or there might have to reveal the source code (de Fine Licht & de Fine Licht, 2020).

However, through their analysis, the authors concluded, that in terms of transparency, more is not always better. Traditionally, the assumption has been that transparency produces accountability, but in the age of Big Data and algorithmic decision-making, researchers and policy-makers have to rethink what transparency should actually look like (Kempeneer, 2021) Opening up the code and explaining the justifications of the decision may be harmful – it may begin a post-decision discussion that will result in more controversy than good for the public. Of course, obscurity in decision-making is also harmful (Kempeneer, 2021). Here, the justifications are also often not genuine. Second, the decision-makers can focus on what they need to achieve throughout the process and ask questions and consult peers if they are not fully monitored (de Fine Licht & de Fine Licht, 2020). Kempeneer proposes that relational transparency might be useful for future data-driven decision-making, in such a way that mutual understanding and learning between agenda-setters and objects of decision-making, rather than unidirectional disclosing of information by the institution may lead to a harmony of accountability (2021). This means that there needs to be constant communication between stakeholders and citizens and acknowledgment of the skills other collaborators can bring to the table (Kempeneer, 2021). Therefore, they conclude that being transparent in the goalsetting phase of the decision-making process and being open about the rationale of their use of data and the resulting decisions is best to ensure public support for the decisions made (de Fine Licht & de Fine Licht, 2020).

Further, transparency plays an especially significant role in automated-decision making, which was partly discussed in the prior AI dimension. To reiterate here, it is highly important to be transparent to what degree self-learning systems are used and how they are used to not cause concerns for citizens, where public opinion may be turning negative. Therefore, a recent European Commission report highlighted the need to make automated decision-making systems more explainable and therefore, transparent (Starke & Luenich, 2020). Also, Dingelstad suggest it may also be beneficial to educate civil servants or employees early on in their career on what data transparency means and the necessity to focus on it during their work (Dingelstad et al., 2022)

To sum it up, the characteristics of transparency include making the process visible and publishing relevant data and results. However, it is also essential to consider what and to what extent to publish and be transparent as it became clear through de Fine Licht's research. Focusing on the rationale of data-driven decision-making and making these aspects public appear to be the most valuable. Further, it is especially important to be transparent when it comes to automated decision-making systems, as the underlying technologies are not commonly understood by the public and may therefore lead to resistance by the public. A possibility to do this would be through relational transparency, which means that both parties' knowledge and positions are explicitly acknowledged and not just unilateral and one-sided publications.

3.10 Ethics

The next dimension that the literature review uncovered, is the dimension of ethics. The characteristics here are the responsibility of stakeholders in the decision-making process, the consideration of risks, and the inclusiveness of the collected data.

3.10.1 Responsibility

Data and especially Big Data change the decision-making process. According to Herschel and Miori, Big Data has the potential to reduce ethical considerations in decision-making, but ethics must be kept part of the conversation. Ethics is valuable because it "helps us to frame our arguments about what is right or wrong using logical, rational arguments" (2017, p.35) and thus ensures the support and trust of the citizens in a decision or policy.

Thus, once a government has access to large amounts of data, they are entrusted with a responsibility to handle and utilize these ethically for decision-making. While in the digital age, Big Data allows organizations to rapidly collect, assess and exploit information, they need to do so responsibly and thus, ethically. Ethics is important as it can inform the ways of handling the data (Taylor, 2020). According to Herschel and Miori, this entails not compromising an individual's privacy by giving third parties access to such data (Herschel & Miori, 2017). Plus, Dingelstad et al. argue that being unethical means using data analysis negligently or uncritically. To overcome this, responsible innovation could be a relevant factor. To do this, one can map ethical and societal aspects to incorporate them in the design of the data analysis (2020).

Further, a problem that can occur by datafying decision-making is that Big Data may shift the focus away from the individual's ability to make moral judgments, as in is right or wrong, towards a machine or algorithm. This implies that a person's assessment of the situation is moral, while a data model cannot do that. This shifts the responsibility of morality and ethics towards the person in control of the data and the algorithm and they need to be examined and held accountable for the actions of the data analyses. Therefore, one must know who the relevant stakeholders are and what their level of power in the decision-making process is (Herschel & Miori, 2017). Here, this implies a close connection of this dimension to the dimension of privacy and data protection.

3.10.2 Consideration of risks

Ethics can also refer to the risks that the change toward data-driven decision-making can infer. This is especially relevant to automated decision-making. Van Zoonen highlights cases of mistakes in social policy based on dataification in the US, where millions of people were wrongly accused of fraud, Paul (2022) addresses the Dutch welfare scandal and the Australian robodebt scheme, where automated decision-making failed citizens spectacularly. One argument is that the dataification of policymaking resulted in a "digital poorhouse" (van Zoonen, 2020), as already marginalized groups of people were wrongfully accused because of the chosen indicators in the data science project. Another aspect that refers to ethics is surveillance and the all-encompassing role government can play once they start using citizens' data. This will further be discussed in the 'legitimacy' chapter of this project (van Zoonen, 2020). Also, Herschel and Miori again point to the role of the stakeholders who can knowingly employ data projects to their own interests (2017).

3.10.3 Inclusiveness

Another characteristic is that the data has to be inclusive. This implies that the data includes all data subjects that the decision is made about (van Veenstra, 2020). This represents a key concern in the governance of big data sources. The data is being used selectively and may not represent the entire population. However, this is crucial to making a good and sound decision for all. Therefore, sampling needs to be good and encompass all relevant data (Mureddu et al., 2020).

This is also highly important for the use of novel sources of data, such as the Internet of Things or social media data which could also be used for the decision-making process. Longo and Dobell warn that the volume of Big Data should not automatically be translated to it being representatively collected data. There are those who are digitally invisible and their data may not be integrated (2017). Further, some parts of society are overrepresented in digital data, usually, younger people who are using the Internet and Social Media, but also those who are highly educated (Ceron & Negri, 2016), (Longo et al., 2017). Pencheva et al. acknowledge that in terms of social inclusion there exist limitations to the potential disparity in technological accessibility among individuals, with those most in need of empowerment having the least opportunities to engage with technology. In fact, within the current data ecosystem, this situation could potentially generate further strengthen disparities in digital resources between those who possess the data resources and those who do not. This also coincides with the risk that the complex nature of the democratic process discourages citizens from participating in policy development from the start (2020). Hence, the democratic nature of data-driven decision-making may be overhyped and overstated. A lot of data does not automatically mean inclusive data.

In summary, it is necessary to keep the challenges of ethics in mind. Big Data can shift the power dynamics toward the stakeholders involved and they need to be held accountable to protect individuals' rights. As there have been mistakes in past applications of data analysis and automated decision-making, this is highly relevant.

3.11 Taxonomy

The objects found in the literature were aggregated into dimensions and characteristics to develop the final taxonomy. The key barriers and drivers of each dimension were allotted to the characteristics and added to a table that represents the final taxonomy. This table can be seen below. The taxonomy also represents the code tree for the content analysis for the case studies in the artifact evaluation.

Dimensions	Characteristics		
Data collection	**Data Access and availability** More data does not automatically lead to better decisions	**Infrastructure for collection** Need for a cohesive technical infrastructure; Challenge of a siloed collection structure and different collection formats	
Data Quality	**Accuracy** Achieved through expansion of databases, better data visualization, more in-depth analytics; erases uncertainties; Danger of a privacy trade-off	**Reliability and Validity** Trust in an indicator, need for reliable indicators; Faulty data results in faulty decisions	**Representativeness** Incomplete data is often ignored; False Confidence in Big Data; Danger of data gaps
Skills and competences	**Role of decision-makers** The skills in the decision-making process need to match the data provision	**Ability/ Data literacy** Need for better education and skills development in the public sector	**Collaboration** Challenges in coordination and collaboration with new providers; Inexperience; Privacy trade-off
Data Analytics application	**Data infrastructure** Sound and cohesive data infrastructure necessary for analysis	**Operational capability** Better decisions through data analytics and data modeling, opportunities through policy analytics	**Interpretation** Data is not value-neutral; Correlation is not causation
Automated and AI decision-making	**Suitable types of decisions** Simple, recurring decisions with clear, fixed, and finite criteria	**Role of humans** Some degree of human supervision is still necessary	**Bias** Danger of introducing bias already in the training data
Data Sharing	**Interoperability** Need for interoperable systems and financial investments to implement these	**Stakeholders** Role of stakeholders involved in the process needs to be assessed and data sharing incentivised	
Legitimacy	**Institutional Contexts** Clear institutional mandate for all stakeholders involved	**Legal Context** All data collection, dissemination and use needs to be within legal mandates	**Data Privacy and Protection** Ensure data privacy and protection of citizen's data
Trust	**Public Perception** More public support through data, public opinion can be evaluated easier	**Politicization** Data can be used to support pre-existing political agendas	
Transparency	**Reporting** Opportunity to make citizens understand rationale of decisions through regular reporting of the relevant data that underpins decisions	**Timing and extent of transparency** Difficult to find the right timing for transparency; more transparency is not automatically better; important in ADM	**Open Data** Use of dashboards to communicate decisions to the citizens
Ethics	**Responsibility** Big Data shifts the power dynamics toward stakeholders	**Considerations of Risks** Datafication can result in wrong decisions, this needs to be mitigated	**Inclusiveness** The data samples need to include all data subjects

Figure 4 Taxonomy for government data-driven decision-making (Source: Author)

4 Analysis-Artifact evaluation

The literature review has provided the answer to the question of what the main dimensions and characteristics are that define data-driven decision-making, but also what the main challenges and opportunities of government data-driven decision-making are, as presented in the artifact. However, in line with Nickerson et al.'s approach, this framework still has to be tested through an application which was done by applying the framework to three cases of data-driven decision-making strategies during the Covid-19 pandemic governance, in Germany, the UK, and Sweden. These three cases will show the applicability of the developed framework and further discuss the question of what the challenges and opportunities of government use of data for decision-making are by comparing the results of the analysis to the challenges and opportunities found in the literature review and answer the question how the framework could be used to evaluate data-driven decision-making in Covid-19 responses. The following chapter will present the results of this analysis.

4.1 Data collection

The first domain of the requirements perspective is data collection, which is characterized by data access and data availability, plus the infrastructure in place for the data collection.

4.1.1 Germany

The Covid-19 pandemic presented unprecedented challenges to decision-makers. The data changed rapidly, and decisions had to be made fast to contain the spread of the virus. The situation was volatile and dynamic, which resulted in a lot of problems regarding the availability and access to the relevant data at the right time. In Germany, sometimes there would be new recommendations every 6 to 8 hours depending on the availability of new data. This could be seen in the example of school closures (Kuhlmann et al., 2021b). There were several different actors on different levels of government that made up the infrastructure for collection. The local health agencies play a very important role: Local health agencies conducted Covid-19 testing and contact tracing and collected this data. They also collaborated with non-profit organizations and private laboratories were established to facilitate testing. Infection data was collected by these agencies and transmitted to the state health administration, which then shared the raw data with the RKI (Steytler, 2021).

Focusing on the data level, in effect, the data on infections was handled like this: People would get tested in official testing offices, who in turn would send their numbers to the responsible Gesundheitsamt every day. They would document the cases and send their numbers to the Robert Koch Institute (RKI). The RKI is Germany's federal health agency and thus the central actor in pandemics, originating from the now defunct Federal Health Agency. The RKI collaborates with regional and local actors in the Laender on a subnational level, but also with the World Health Organization (WHO) (Steytler, 2021). The RKI is also the relevant actor in utilizing statistics and numbers to inform decision-making: It is their task to inform political institutions, (including the Bund) based on their publications, but also provide technical assistance to local health agencies (Steytler, 2021).

In terms of the infrastructure for collection, there was a lack of standardization of the captured data. There was a variation of granularity and level of detail in the health data that was to be stored: At the most granular level it would be individual patient-level data and the least granular is aggregated summary-level data. Further, there was a variety in data format: It could be imaging data or even highly ordered clinical codes, or numerical outputs of assessments from laboratories. Sharing data in different formats and different levels of granularity hindered the interoperability of the decision-making procedure (Dron et al., 2022).

There were problems with data capture, such as non-standardized data collection and encountering heterogeneity in data terminologies, plus a siloed data infrastructure. Further, the data was often not inclusive as not everyone went to get tested, and not everyone had to go to the hospital where there would have been standardized testing and coding of the data (Dron et al., 2022).

4.1.2 UK

The analysis identified several issues with poor data access in the UK. One of the reasons was poor data sharing, which will be addressed in detail later, but also poor integration of data flows that were gathered from across health and social care sectors, both at a national and local level, for example, hospitals or testing agencies, and then also major issues in integrating the data from the four devolved states Northern Ireland, Wales, Scotland and England (Secretary of State for Health and Social Care, 2021). Additionally, the decision-making chain of command was complex, and responsibilities were not clearly allocated which further hindered the access to the data.

The UK was set on collecting five types of indicating data to base decisions on. These were case rates, case rates over 60 years old, change in case rates, positivity rates, and NHS metrics (Secretary of State for Health and Social Care, 2021). However, the evaluations acknowledge that decision-makers made a huge mistake early on in the pandemic to stop community testing (Secretary of State for Health and Social Care, 2021). This resulted in virtually zero data availability and no further restrictions were imposed for a long time and affected the outbreak management badly (Secretary of State for Health and Social Care, 2021) and (Health and Social Care and Science and Technology Committees, 2021).

Another point was the availability of real-time testing data, which was crucial for prompt and effective response to outbreaks of Covid-19, meaning the earlier the data is available, the better the response will be. However, this was not available and a common complaint with local decision-makers in the UK (Public Administration and Constitutional Affairs Committee, 2021b).

One major complaint, which will be discussed in several chapters of this analysis regarding the UK, was that the response was centrally led by London rather than letting local actors make their own, informed decisions. Gathering all data in the central government in London meant that data was rarely available to the local decision-makers and there was little localized data available where it was needed (Public Administration and Constitutional Affairs Committee, 2021a). In the UK, SAGE was responsible for collecting timely, coordinated scientific or technical information to present to the decision-makers across the UK government (Public Administration and Constitutional Affairs Committee, 2021a). NHS Test and Trace supplied the testing data until communal testing was stopped for a while (Secretary of State for Health and Social Care, 2021). While the collection infrastructure was disparate in the beginning, the establishment of a designated agency to manage data collection and distribution was set to make the situation better, so they set up the Joint Biosecurity Center (JBC). Their stated aim was to: "provide evidence-based, objective analysis, assessment and advice to inform local and national decision-making in response to covid-19 outbreaks." (Health and Social Care and Science and Technology Committees, 2021, p.26). This also included bringing together the relevant datasets from local authorities or hospitals, prisons, and so forth and supply all authorities and decision-makers with the necessary data in a timely fashion (Health and Social Care and Science and Technology Committees, 2021).

While there was existing infrastructure that could have been used for data collection and dissemination, the government set up new data collection infrastructure which operated separately from existing public health systems. It has been noted that the existing systems were undervalued, despite having robust expertise governing them, and they were good for managing data flows. By setting up new systems, a fragmented landscape was put in place that disconnected national and local data collection and was hardly accessible (Public Administration and Constitutional Affairs Committee, 2021a).

In the beginning, even Excel spreadsheets were used to collect the data, where testing center employees would manually transpose data into these spreadsheets, as there was no good system in place (Public Administration and Constitutional Affairs Committee, 2021a). To sum it up, the UK's data collection was hindered and slowed down by a lack of data availability, a fragmented data collection infrastructure, and difficult access to data for all the relevant actors. It became clear that better leadership would have been needed in the Department of Health and Social Care to improve the data collection from across the entire health system (Public Administration and Constitutional Affairs Committee, 2021a).

4.1.3 Sweden

Especially in the beginning, little data was available in Sweden, which resulted in mild measures, as recommendations were given (Wang et al., 2022). The main issue with data collection was the lack of uniform testing in Sweden (Andersson et al., 2022), with only 180 tests done in the first 5 weeks of the pandemic (Pashakhanlou, 2020). The testing and collection infrastructure was very slow to develop, as PHA was unsure if the resources for setting up such a system were worth it. The assumption at the beginning of the pandemic was that the spread of the virus would slow down on its own (Andersson et al., 2022). Further on in the pandemic, more data became available, also from hospitals, which was gathered in simple tables (Wang et al., 2021). Data access was improved by fast-tracking the processing of statistics and data requests from major data owners, such as the organizers of clinical trials. Also, the testing responsibilities to collect data were reallocated to the regions (de Bienassis, 2022).

To gather the number of infections, there was also a mobile hotline (+1177 Vardguiden (Folkhalsomyndigheten, 2020 and 2021)) that was built on the existing Swedish mobile health infrastructure. However, as the author knows from personal experience, the hotline seized working in early April 2020 due to an overwhelming number of calls. This essentially meant that one could not get tested anymore. This also impacted the collected numbers of infections.

There were no mobile applications to gather data in Sweden. The reports highlight that the PHA saw problems with data privacy with applications in other countries, that there was not sufficient data and research to understand the benefits of such an app and that it would take a lot of resources to set one up and that is why it was unnecessary to have one (Folkhalsomyndigheten, 2020) and (Folkhalsomyndigheten, 2021).

4.2 Data quality

The next domain of the requirements perspective is data quality. The relevant characteristics that signify data quality are the absence of data gaps, the accuracy of the data, and the validity and reliability of the data to underpin the decision-making.

4.2.1 Germany

In Germany, the topic of data quality was discussed less. While the KResCo identified several potential pitfalls when it comes to the accuracy, validity, and reliability of the collected data. They mainly address that the data was not always timely. During the pandemic, the number of infections changed every day and decisions had to be adapted very quickly (KResCo, 2022a).

During Covid governance, there had to be a trade-off between timeliness and data quality. If one wanted to have the most accurate data, it took more time to consolidate the data. However the virus moved quickly, and it was necessary to make these choices on containment or restrictions as rapidly as possible to be ahead of time (KResCo, 2022b).

KResCo also identified that there were data gaps, because the data such as the numbers of infections or hospitalized Covid positive people, did not arrive at the decision-maker fast enough. This meant that the data were of lower quality because numbers were simply not accurate (KResCo, 2022b). To make the data of higher quality, it would have to be more timely, and always at the same granularity. Health data varies in granularity: The most granular level would be individual patient-level data and the least granular is aggregated summary-level data. Therefore, there was a variety of granularity that influenced the data quality (Dron et al 2022).

In terms of reliability and validity, the analysis identified that one of the major factors of success was the data collection and storage in databases. If the databases were solid and manageable, the data could be more valid and reliable. Here, it also counts to define the criteria of data collection clearly and definitely for all levels of decision-making (KResCo, 2022b).

The danger of data gaps was a common problem during the pandemic, often caused by problems with data capture, such as non-standardized data collection and encountering heterogeneity in data terminologies, plus a siloed data infrastructure (Dron et al. 2022).

4.2.2 UK

In the UK, data quality in terms of the three characteristics of data gaps, accuracy, and validity/reliability, there was plenty of discussion in the official evaluation reports and data from the accompanying sources.

One of the main problems in terms of data quality was the lack of data that the UK had access to in the early stages of the pandemic. In the beginning, there was limited testing and there simply were not many testing capabilities, the only tests that were administered were for UK citizens who had to be administered to hospital (Secretary of State for Health and Social Care, 2021). Also, the testing was outsourced to private sector actors, who struggled to set up their businesses and transfer the data to centralized offices (Hanson et al., 2021). This resulted in poor quality of the data, as the data was limited to the hospitals. Therefore, decision-makers and scientists did not know where the virus was spreading, and no accurate decisions could be made. However, the situation improved beginning in May 2020, when the so-called ONS Infection survey was put in place to streamline the quality of data through better processes (Secretary of State for Health and Social Care, 2021). This coincides with validity and reliability problems through the challenges in integrating and processing data. Test and trace data often had gaps due to delayed input from the regions and key information was not consistently and uniformly integrated and processed (Public Administration and Constitutional Affairs Committee, 2021a).

Additionally, at the beginning of the pandemic, when the data collection infrastructure was not in place yet, ad hoc systems to process and collect data were created by the NHS which led to data quality problems. This encompasses changing definitions and inclusion criteria, which raises concerns about data validity and reliability (Public Administration and Constitutional Affairs Committee, 2021a).

Further, the testing data was not definitely accurate (Public Administration and Constitutional Affairs Committee, 2021a). PCR tests sometimes present false negatives and positives which negatively impacts the overall accuracy of the data that underpins decisions and policies. The SAGE panel published a report that stated that “the sensitivity of the swab test (rt-PCR) is not 100 percent, and the probability of a false negative result changes over the time since exposure (infection)” (Public

Administration and Constitutional Affairs Committee, 2021a, p.12). This led to criticism of policies made by the UK government, as some said these flaws need to be acknowledged by the government.

Another large gap in the data was the fact there was insufficient evidence to understand the often disproportionate impact of Covid-19 on minority groups. In the UK, the death registration and certification process does not record ethnicity, which leads to an overall lack of data on Covid-related mortality by ethnicity. To address this gap, new measures were introduced in October 2020 and Hospital Episodes data were used to research the factor of ethnicity on mortality and provide decision-makers with more accurate data to address these disparities (Science and Technology Committee, 2021).

Overall, the statistical evidence input was of high quality and worked well under the pressure and demands of an ongoing global pandemic, even though the disparities in collaboration also affected the quality of the data and statistics, for example, due to delays (Public Administration and Constitutional Affairs Committee, 2021a).

4.2.3 Sweden

Similar to the problems with the data collection, this also impacted the data quality in the Swedish Covid-19 response. However, little testing was done throughout the pandemic in Sweden (Wang et al., 2022a). Widespread testing would have been essential to gather representative data on the spread of the virus.

Testing was done by individuals calling a hotline (4411) and asking to register for a Covid test. However, based on the author's personal experience, the hotline ceased to function in early April 2020 due to an exceedingly high volume of calls. Consequently, individuals were no longer able to undergo testing during the first wave of Covid. That means data was not representative anymore and there were wide gaps in the number of infected (Wang et al., 2022b). Further, the head of the PHA, Anders Tegnell even doubted the usefulness of testing in general in a television appearance (Andersson et al., 2022), which is in stark contrast to the fact that he usually stated that he only based the strategy on data (Regeringen, 2020).

The poor data quality in Sweden directly resulted in the lack of action and interventions by PHA. This is exemplary by the fact that the PHA relied on foreign recommendations and hearsay rather than their quality data. When the Chinese government let the WHO know that there was no clear data to support the idea that the virus passes easily from person to person, the PHA took this information by heart and subsequently did not impose any restrictions (Pashakhanlou., 2020).

4.3 Skills and competencies

The second domain of the requirements domain is skills and competencies. This contained three distinct characteristics. These are the changing role of decision-makers, ability, and data literacy, plus the collaboration between those stakeholders that were included in the decision-making process during Covid-19 policymaking.

4.3.1 Germany

Collaboration between stakeholders and the interplay between decision-makers and scientific data providers was essential to data-driven decision-making during the pandemic. Kuhlmann et al even state that "the interplay between policy-makers and scientific data providers, as well as the use of data for the preparation and legitimation of decision-making processes, has never been more pronounced than during the COVID-19 crisis" (2022, p.278).

In Germany, the overarching goal of decisions was to keep the healthcare system from overload. Therefore, the decision-makers had to work closely with different actors, depending on which level of government was in charge. At the federal level, for example, the RKI advised the government and the Corona Krisenstab committee as scientific data providers. Formal relationships with scientific data providers from different research institutions plus scientific advisory boards of the ministries, such as the local Gesundheitsamter, and the Federal Ministry of Health facilitated the provision of data for the decision-making process. However, when it came to determining measures, third-party, external providers were used, specifically to provide epidemiological and virological expertise. Additionally, physical modeling and forecasting were outsourced as well. This reliance on outside expertise led to criticism of Germany being an 'expertocracy' (Kuhlmann et al., 2022). This will become relevant again in the Trust section of this framework.

The roles of political decision-makers changed: Especially in the early stages of the pandemic, both decision-makers and data analysts needed to get used to a novel mode of communication. Challenges and uncertainties arose regarding the shared expectations of both parties were observed. A study showed that there was a lack of mutual understanding and there was no common language between the administrative and political side and the data providers (Kuhlmann et al., 2022).

Additionally, the situation and subsequently the corresponding data changed quickly, especially during the initial stages of the pandemic in early 2020. The situation was volatile, the data infrastructure was not set up yet which added complexity to weighing and interpreting the data. Kuhlmann argues that "in this situation, scientific statements characterized by contextualization and deliberative wording contrasted the demand of political-administrative decision-makers seeking to obtain unambiguous findings and precise recommendations" (2022, p.278).

While data providers had to emphasize that there would always be uncertainty regarding the forecasts, this was hard to grasp for the political side with less data literacy. Therefore, it is arguably also quite difficult to determine to what extent decision-making was influenced by the data analysis, especially in early 2020. However, later on, there was a clear convergence of understanding between collaborators in scientific data and political decision-making (Kuhlmann, 2022).

Another challenge was an information overload, which necessitated a high level of informational capacity on the administrative-political side. For them, it was unprecedented to deal with such a level of information that they received from the data providers. They faced difficulties in "digesting and processing all crisis-relevant information inputs adequately" (Kuhlmann 2022, p.278), which led to bottlenecks in decision-making (Kuhlmann., 2022). Finally, the concept of task forces proved a successful intermediary option. These were set up with experts from interdisciplinary backgrounds, be it medical, sociological, or business, to aid with the decision-making process and were each able to add expertise to the existing data (KResCo, 2022b).

4.3.2 UK

In the UK, key decisions were made by the center of government, but the imperative to act still sits with local leaders and frontline staff (Public Administration and Constitutional Affairs Committee, 2021a). One of the main issues of data-driven decision-making that the analysis identified, was a lack of clear allocation of responsibilities. Therefore, collaboration was difficult, and lagging. A variety of stakeholders were involved from data collection to the final decision-maker, and even this was complex in regards to the imposing of restrictions for all four devolved UK nations, Northern Ireland, Scotland, Wales, and England.

Rather than relying on its public health agency Public Health England (PHE), the UK utilized and expanded upon its pre-existing national scientific committee known as the Scientific Board for Emergencies (SAGE). SAGE quickly became the key actor in British decision-making, and it said that the first lockdown in March 2020 was directly influenced by a modeling paper presented by SAGE members (Hanson et al., 2021). SAGE and its subcommittees were in direct contact with a variety of scientific advisors to assess the data and make informed decisions based on the provided scenarios (Secretary of State for Health and Social Care, 2021). SAGE had to cooperate with the Joint Biosecurity Centre (JBC), which is a Directorate of NHS Test and Trace that is located in the Department of Health and Social Care (DHSC). The JBC was supposed to be in charge of gathering, interpreting, but also analyzing a wide range of data (Secretary of State for Health and Social Care, 2021). Effectively, however, their role was unclear and their jurisdiction to manage data flows across the government was not effective (Public Administration and Constitutional Affairs Committee, 2021a).

For testing data, the NHS outsourced the work that was overseen by NHS Test and Trace to the private sector (Hanson et al., 2021), even though this is barely explicitly mentioned or clarified in the official government papers. However, this collaboration took some time to run efficiently.

Further, the government employed multiple sources of evidence to assess the economic ramifications of the pandemic, and they consulted the Office for National Statistics (ONS) and forecasts and projections released by the Office for Budget Responsibility, the Bank of England. They also collaborated with other relevant private actors to gather mobility data or real-time information from the NHS COVID-19 app (Secretary of State for Health and Social Care, 2021).

4.3.3 Sweden

In Sweden, there were fewer stakeholders involved. This is partially because Sweden is a smaller country, but also because of its centralized governance structure. The main actor in terms of Covid-19 decision-making was the Swedish government, the Riksdag, which receive data input, guidance, and scientific advice from various key entities: First and most notably was the Public Health Agency (PHA), which was comprised of individuals with interdisciplinary backgrounds, such as politics, healthcare, and research. This is the institution that was headed by Sweden's chief epidemiologist, Anders Tegnell, who quickly became the key player in Sweden's pandemic decision-making. Next, the National Board of Health and Welfare was in charge of ensuring an adequate number of ICU beds in hospitals. Finally, the Swedish Civil Contingencies Agency was tasked with overseeing the potential long-term societal impacts of the pandemic and producing public information campaigns (Ludvigsson, 2020). While the responsibilities were quite clearly allocated, in effect, in terms of decision-making, the PHA, and Anders Tegnell at its forefront, became the sole deciding player. In effect, Sweden completely delegated the decision-making to the expert authority PHA, and politicians essentially played no role in Swedish decision-making (Andersson et al., 2022).

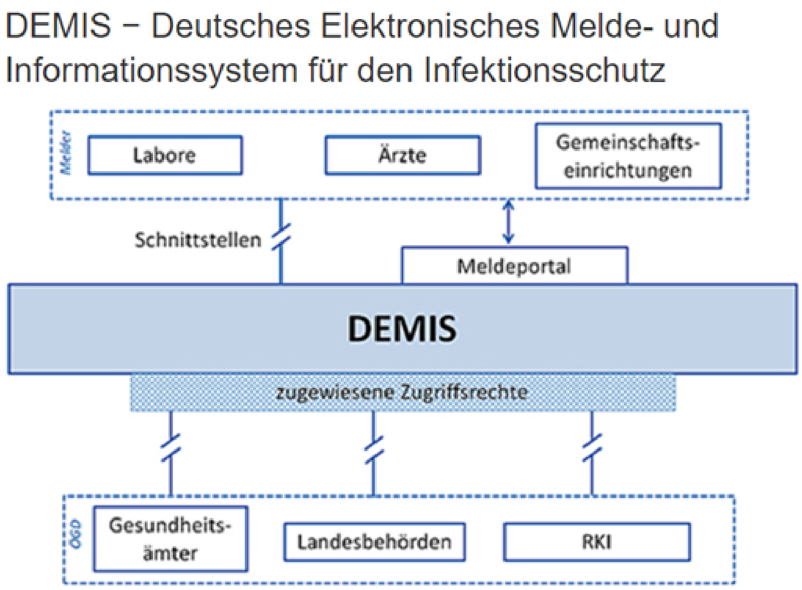

Figure 5 DEMIS (RKI, 2021)

In response to criticism regarding the dominating role of PHA, a formal advisory board was set up in April 2020, but there are no official publications regarding their work and their influence remains obscure (Hanson et al., 2021).

4.4 Data analysis application

The next dimension of data-driven decision-making is the actual data analytics application. This was characterized by the data infrastructure, the interpretation of the data, and the operational improvement of data analytics.

4.4.1 Germany

These processes are represented in the data management infrastructure that was set up, which in Germany is called DEMIS/DEMIS-SARS-CoV-2. Here, we can see that laboratories were able to send their information to the DEMIS adapter, which manages the data and ensures it is sent to the correct Gesundheitsamt. As represented in the figure below, the DEMIS allows the Gesundheitsamter, the Landesbehorden – those government agencies that would need access to data for domains other than health- and the RKI access to the stored data. This is supplied by the testing laboratories, doctors, and other communities that have testing capacity (RKI, 2021).

The reports identified that there was a significant time delay in analyzing, preparing, and providing relevant data (OECD, 2022); (KResCo, 2022b), (KResCo, 2022a). It is important to have uniform criteria for data collection to enhance the data infrastructure and loading process (KResCo, 2022b). A prominent limitation was that there was a lack of machine-readable provision of raw data. This led to slow or halting responsiveness in data management and especially made the reuse of data very difficult (Kuhlmann et al., 2021). It was important to further develop databases to store data and make it more readily available for decision-making, but also so that the reporting of data and subsequently information to the decision-makers and the public could be faster, which was a struggle in Germany. Further, there was a lack of initiative to include data or know-how from academia (KResCo, 2022a). For Germany, there was a distinct lack of information about data analytics applications or interpretation to be found in the reports.

4.4.2 UK

The data infrastructure in the UK, especially at the beginning of the pandemic was cause for concern. In theory, the Cabinet Office is responsible for governing data across the government. However, they failed in allocating the responsibilities in a streamlined and aggregated fashion, especially at the beginning of the pandemic (Public Administration and Constitutional Affairs Committee, 2021a).

Rather than using modern data systems that are specifically designed to process big data sets, testing data was collected and stored in Excel spreadsheets. Here, positive Covid cases were manually transcribed into these Excel sheets. This was also prone to errors by the persons in charge of adding large numbers into Excel. This of course is also not in line with national statistics guidelines (Public Administration and Constitutional Affairs Committee, 2021a). The evaluation even revealed that some of this testing data were written down on pieces of paper rather than kept digitally (Public Administration and Constitutional Affairs Committee, 2021a).

However, this does not mean that digital public health data systems did not exist before 2020. But these systems are fragmented and therefore in early 2020, there was no coherent statistical overview of the public health in the country and relevant data was not available in a central infrastructure that decision-makers could pull data from to inform their decisions. Rather this meant that there was an additional effort for scientists and statisticians to allocate the data they needed, to supply the demands of the decision-makers (Public Administration and Constitutional Affairs Committee, 2021a). This fragmentation also exists due to rapidly changing national guidelines to manage Covid-19 which resulted in many different actors and responsible entities. For example, the NHS and Public Health England both publish completely disparate statistics on vaccination statuses (Public Administration and Constitutional Affairs Committee, 2021a), and patient records, which include some of the most important data for Covid-19 decision-making, exist in different national bodies, like NHS foundations trusts and NHS trusts, but also in the digital records of general practitioners and social care providers (Public Administration and Constitutional Affairs Committee, 2021a). This is exemplary of the fragmentation in data provision architectures. Therefore, the data revealed a need to have one single, consistent, interoperable framework for information governance in the UK health sector (default 12). This also includes the idea that statisticians and data analysts are allocated centrally in the Department of Health and Social Care and can aggregate the data that they can pull from different sources, but process these centrally. However, this system is not in place yet (Public Administration and Constitutional Affairs Committee, 2021a).

In terms of interpretation, the data analysis revealed several points. Politicians in the UK have stressed that they are intent on, as they call it, following the science. However, the evaluation reports stressed that in science there is not a single correct interpretation of the data. The Royal Society stressed in their statement for the inquiry that "at the frontiers of science, there is always uncertainty, and to pretend otherwise would be foolish" (Public Administration and Constitutional Affairs Committee, 2021a, p.12). During Covid-19, British decision-makers constantly had to evaluate between public health and the needs of the economy. Here, there were many connected, but also competing considerations that implicated how the data was evaluated, meaning the parameters for data analysis depend on the aims of the analysis (Public Administration and Constitutional Affairs Committee, 2021a).

Data analysis also means testing and calculating the outcomes of different scenarios. These scenarios could be the implications of only imposing social distancing recommendations, and no self-isolation measures versus a scenario that imposes testing, tracing, and subsequent self-isolation for UK citizens. In the UK, to assess the impacts of measures in place, modeling of the data was done by NHS Test and Trace. Their impact modeling has estimated that the policies that were made according to their data, such as testing, tracing, plus self-isolation had reduced the R number from March 2020 until October 2020 by around 0.3-0.6, meaning their decision-making on the data modeling scenarios was statistically impactful and effective (Secretary of State for Health and Social Care, 2021). The UK also activated expert academics to provide input on the mathematical models to further improve the technical calculations (Public Administration and Constitutional Affairs Committee, 2021b).

4.4.3 Sweden

In the reports, the use of data and data analysis applications is covered fairly extensively, mostly in terms of operational use and the modeling of scenarios, and the interpretation of these models, which played a key role in Swedish decision-making. In terms of data infrastructure, there was little data available.

In terms of data infrastructure, there was a national case reporting system called SmiNet introduced in 2004, where doctors, hospitals, and the cases reported through the 1177 hotline could be gathered and sent to PHA (Folkhalsomyndigheten, 2021a). As stated prior, the PHA was the responsible agency when it came to data analyses and modeling. They published reports called "Scenarier för forstatt spridning" – Scenarios for the upcoming spread, 11 reports were published beginning in 2020. The reports contained modeling for how the virus was expected to spread in the upcoming year (Folkhalsomyndigheten, 2020). The underlying modeling is explained in detail in these reports.

The Folkhalsomyndighet, the Swedish Public Health Agency subsequently made their decisions on containment measures or lack thereof, and recommendations based on these scenarios. The PHA was analyzing cases of Covid-19 in Sweden (Regeringen, 2020). The model used was an epidemiological model called VirSim, a compartmental model that divides the population into the categories of Susceptible, Exposed, Infections, and Recovered (SEIR). The compartments signify proven and unproven positive cases and respect age groups. They used population data from Statistics Sweden (SCB) and infections data from SmiNet (Folkhalsomyndigheten, 2020).

In the figure below, an example of the modeling can be seen. The models were calculated by region, the figure below shows the modeling for the Skane region for the period August 2020 until March 2021, based on scenario 0, and calculates the number of infections against the upcoming time.

It becomes interesting, when considering these models, what was interpreted from them and what decisions were taken based on these scenarios. The Folkhalsomyndighet stated that they chose not to impose lockdowns or similar restrictive measures on the Swedish population based on these models.

However, they have chosen to base these decisions only on the best-case scenario, and in retrospect, it is known that the scenarios did not reflect the actual spread of the virus. The interpretation becomes controversial and arguably the PHA consistently underestimated the risks of the coronavirus spreading in Sweden which might have been because of erroneous data analyses. Anders Tegnell later revealed that based

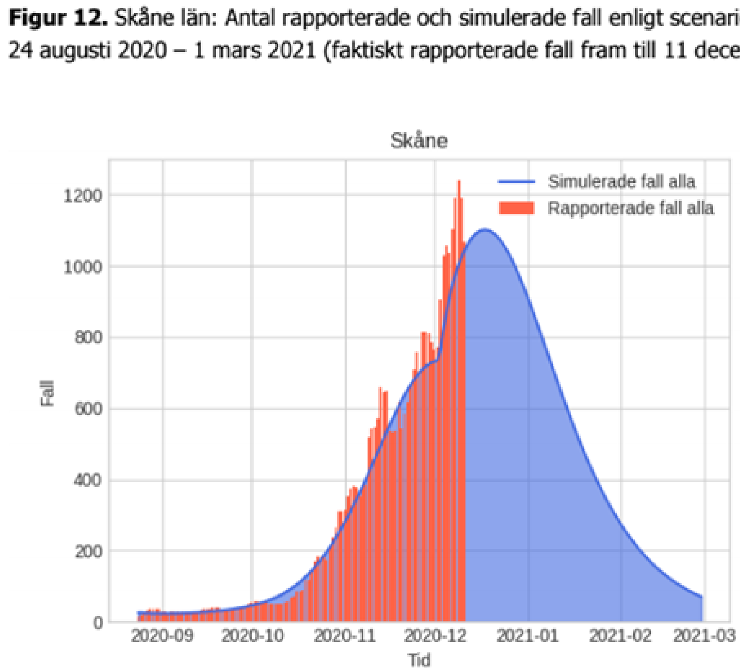

Figure 6 Scenario modeling in Sweden (Folkhalsomyndigheten, 2021b)

on their modeling, the virus would jump between localized hot spots, back then Northern Italy and Wuhan in China, rather than spread widely throughout the world (Pashakhanlou, 2022).

Other than not imposing lockdowns, the PHA also based other decisions on their interpretations of the data. They recommended against using face masks, as they stated there was not enough evidence to support their efficacy (Pashakhanlou, 2022), they opted against contact tracing as they did not want to implement the data infrastructure for it as it would have been too time-consuming (Folkhalsomyndigheten, 2021a).

When seeing the importance of the decision taken not to impose lockdowns or take any restrictions to mitigate the spread of the virus based on this data, it is also interesting that the PHA stated in 2020 that they are in fact “very unsure” about the spread of the virus (Folkhalsomyndigheten, 2020, p.8). They further state that it is difficult to calculate for so many regions – Sweden has 25 provinces - and that the computer program used for data analysis had difficulties to find a value that they could calibrate to calculate against the real-time development of the spread of the virus because of many uncertainties (Folkhalsomyndigheten, 2020).

In summary, while the Swedish strategy was so evidence-based, and the PHA consistently reiterated that every decision was based on the data, there was very little effort put into assuring there was solid data infrastructure, and the interpretation of the data was controversial on top.

4.5 Automated and AI decision-making

During the covid pandemic, with such contentious policies, some argue that the integration of AI as a purely statistical and data-driven tool may be useful to convince the population of the usefulness of policies (Saura et al. 2022). AI in combination with statistical models can help to predict outbreaks and possible infections and even the number of deaths. These models have improved health policy because they can predict the movement of people in cities which makes it possible to dictate effective and necessary lockdowns. However, the use of mobile applications to track user locations comes with the question of data privacy infringements, even if the data was collected autonomously. Some argue for the need to regulate the use of AI during Covid, as well, as they say, it controls the population (Saura et al. 2022). However, the results do not make specific mention of automated decision-making or the use of artificial intelligence for decision-making in either country.

Only in the UK, one blog post by gov.uk indicates: Jarrat et al point out that in their evaluation of data-driven technologies for the British pandemic response: "Conventional data analysis has been at the heart of the COVID-19 response, not AI" (Jarratt et al., 2021, p.1). Further, she states that AI has only played a role in health care itself, to aid in the treatment of patients (Jarratt et al., 2021). This shows that from a practical standpoint, the use of automated decision systems or use of artificial intelligence has not been relevant for this case.

Similarly, there was no mention of automated decision-making in terms of AI in the reports and documents, and research through the official government databases for Sweden. Similar to the UK, AI played a role in healthcare rather than the spread of the virus, etc. (Emilsson, 2020).

4.6 Data sharing

The next dimension is data sharing. The characterizations are interoperability and stakeholders involved that collaborated in the data sharing.

4.6.1 Germany

In Germany, actors on different levels of government were key to the pandemic response, especially local and regional actors. Data sharing has to be understood on several levels, between actors on the same level, but also multi-level data sharing which necessitated horizontal and vertical coordination (Kuhlmann and Franzke, 2022). In Germany, mainly established channels were used to share data intergovernmental (Steytler, 2021). On a federal level, the state was limited to monitoring, surveillance, research, plus legislative tasks, while the major tasks of managing the health response, including outpatient and inpatient care, were left to the Länder and local governments (Kuhlmann et al., 2022). Further, local governments had to implement the lfSG at their discretion, plus take over the burden of administrative tasks and knowledge management (KResCo, 2022a).

Even before the crisis, significant shortcomings and obstacles had become evident in the German health data. Departmental silos hindered access to shared databases and cross-departmental data reuse. Rather than being shared with other administrative units, data tended to be hoarded within individual organizations (Kuhlmann et al., 2022). The reports also acknowledge the importance of data culture and the professional backgrounds of the people in the jobs: In some administrative departments that largely comprise legal professionals or individuals with limited experience in data-driven processes have shown less willingness to cooperate and share data. Conversely, departments with extensive practical experience in handling larger data volumes daily, or with backgrounds predominantly composed of data and social scientists, have exhibited greater openness to data-sharing and are less inclined to hoard data. This also required education in data privacy rules as even in data-based operational rationality, there was plenty of uncertainty regarding what data could be shared with who. (Kuhlmann et al., 2022). Further, for the border regions, data sharing was difficult between the countries and local decision-makers had to rely on interpersonal relationships to get information on case numbers (Kuhlmann et al., 2022).

4.6.2 UK

The shortcomings of data-sharing are represented in the evaluation reports. As discussed in the prior chapters, the pandemic created a large volume of new data and these data flows had to be integrated in such a way that all relevant actors have timely access.

The relevant actors in the UK were the NHS including NHS Test and Trace, the Health Data Research Innovation gateway, the UK Health Data Research Alliance, and experts in public health and epidemiology, all working in close connection with PHE at national, regional, and local levels, to feed the data to the Office for National Statistics (ONS) (Secretary of State for Health and Social Care, 2021).

Existing frameworks and various data-sharing channels have been strengthened to support the pandemic response. The NHS Test and Trace operation in the UK has facilitated data sharing down to individual and postcode levels with all councils in the country. Data dashboards have been shared with local authorities to provide integrated, UK-wide Covid-19 data, ensuring consistent access to key metrics for decision-makers in and outside the government (Secretary of State for Health and Social Care, 2021).

Participation in cross-government working groups and calls has further facilitated interoperability. Over time the data-sharing processes have been expanded and improved by the JBC through investments and re-designing of processes. The JBC played a significant role in increasing data sharing functionality, particularly among government agencies such as the PHE, the Cabinet Office, the (ONS) and the NHS, plus with local authorities. They did so by establishing a wide range of Data Sharing Agreements, Memorandums of Understanding, and Data Protection Impact Assessments, also with the goal of quickening the pandemic response (Secretary of State for Health and Social Care, 2021).

The NHS was the major producer of patient data, also through NHS Test and Trace in terms of case numbers. Often new regulations had to be put into effect ad hoc to enable the sharing of for example patient data through the use of Control of Patient Information (Secretary of State for Health and Social Care, 2021).

One major problem was the data sharing between national and sub-national authorities, plus the sharing between the central government in London and the devolved nations, again reflecting the national-by-default modus operands (Public Administration and Constitutional Affairs Committee, 2021a). The interoperability designs were made by the central government and only included local authorities as an afterthought, which caused a lack of data, especially when community testing was stopped in the summer of 2020 (Health and Social Care and Science and Technology Committees, 2021). Also, data-sharing agreements were only signed in mid-February 2020, when the pandemic was already spreading rapidly and hospitals were reporting infection numbers (default 3).

One responsible person from the Science and technology committee states

> “What you had is, for instance, a testing system set up outside that and there was no way in which those test results could easily flow into the public health system. Because different systems were being set up in silos outwith the public health or emergency response systems that we had, there were technical issues with different data systems that were not

> speaking to each other. That was certainly a problem. Secondly, there was definitely a sense of, “You do not really need that data at a local level, and use of information governance where you had to justify. You had to make a case for why you needed the data. There was a lot of energy going into why we needed that data and having to make a case for it, when in the middle of an epidemic that should have been clear. The case should have been that local directors of public health needed that data and local systems needed that data to be effective in our response. I think it is a combination of both.”(Health and Social Care and Science and Technology Committees, 2021, p.24)

Further, local directors of public health did not have access to NHS Test and Trace data on positive cases, mostly due to technical difficulties, but also due to a lack of volunteers and problems with tracing data (Health and Social Care and Science and Technology Committees, 2021). Local authorities also complained about the kind of data they received: They only had access to positive, not negative test cases, and only from August 2020, postcode data was not shared, which meant localization of cases was not possible.

All these points show that there were some issues in data-sharing in the UK, both in terms of the stakeholders involved and their sharing practices, but also in terms of interoperability.

4.6.3 Sweden

Data sharing in Sweden was different from other countries in such as they had one central organization that determined the decision-making during Covid-19, the PHA. Additionally, as stated in the prior sections, there was very limited testing for Covid in Sweden throughout the pandemic. For data sharing, this meant that the limited testing that was done was through a centralized system that was established for the health sector prior to the pandemic (Folkhalsomyndigheten, 2020). There is a system to collect new data directly from the 21 regional and 290 authorities, plus from specific work groups, and expert networks to manage the emergency preparedness processes. Sweden had also established record linkages before the pandemic began, permitting healthcare providers to share data and for this data to be complemented with contextual data (de Bienassis et al., 2022). However, there was no specific digital contact management system through which data could be shared with the PHA (Folkhalsomyndigheten, 2021a), apart from the national case reporting system called SmiNet where doctors, hospitals, and the cases reported through the 1177 hotline could be gathered and sent to PHA (Folkhalsomyndigheten, 2021a). There was little further data concerning the data sharing found in the analyzed data.

4.7 Legitimacy

The next dimension of the framework is legitimacy. Here, the framework contained three characteristics that are Institutional Contexts, Legal Context and Data privacy and protection.

4.7.1 Germany

To understand the institutional context, it is important to understand the way in which the federal level works with the lavender level on decision-making in Germany. This will highlight the dynamics of data provision etc. and the roles that the different actors play in terms of integrating data into the decision-making process. Institutional processes must be organized in such a way that the logic of evidence and data-based decision-making is strengthened without neglecting the logic of politics. Germany has a highly decentralized and fragmented institutional context as a federal country. However, the unity of law, the economy, and living conditions are institutionally protected. This means that there are several mechanisms for the enforcement of collaboration and joint decision-making across institutional borders to ensure the unity of the federation (Kuhlmann & Franzke, 2022).

This also affected some key issues, as in federal systems, usually the federal government has the responsibility to coordinate in a national emergency, whereas states have autonomy in disaster management and healthcare services (Steytler 2021). At the start of 2020, the decisions taken on restrictions were uniform across all Länder, but by April and May 2020, several states began to diverge to address individual concerns, for example, to open hotels again in those states that have a lot of tourism (Steytler 2021). A lot of the relevant decisions were then made by the Ministry of Health, such as what people from what countries were still allowed to enter the country, rules for public transport, and measures in institutions But also gathering data to identify and register infected persons fell under the Ministry's responsibility (Steytler 2021). Additionally, the federal Ministry of Health in collaboration with the Ministry of the Interior set up a crisis management group comprised of medical experts and employees of the RKI. On a sub-national level, the Laender were involved as they are responsible for health matters, but also because they have to implement federal regulations into Land laws. Plus, the Laender was involved in the decision-making process as the Bundesrat had to approve the measures decided on in the Law to Protect the Population during an Epidemic Situation of National Importance (Steytler 2021).

Kuhlmann et al point out that despite the expectancy of a disconnected and rather discretionary action in Germany due to the decentralized nature of decision-making. Additionally, the framework acknowledges the institutional culture that underpins the dynamics of decision-making. In Germany, Kuhlmann et al states that while pandemic management and policymaking were mostly devolved to the states and local authorities, this did in fact not lead to disconnected or discretionary actions, but instead evolved into intense coordination and collaboration across levels (2022).

In Germany, political decisions were largely based on external data providers to the decision-making actors. At the federal level, formal connections with scientific advisory boards with departmental research institutions were established, which facilitated the integration of data into the decision-making process. Political decisions on containment measures were largely based on third-party data providers, particularly those specialized in virology, epidemiology, physical modeling, and forecasts.

Further, there was a lack of understanding of their respective roles. Communication between scientific data providers and political-administrative decision-makers was stilted. There were various points in time when urgent calls were made for both science and politics to reflect on these roles. The interplay of data and decisions became challenging during the pandemic. Some said that scientists and data analysts pushed their own agenda and proposed solutions, even though they had no democratic legitimacy. On the other hand, political actors were expected not to demand too-specific solutions from the data providers, because they still had to balance and weigh normative rules, laws, interpretations of the data, and complex societal interests, for example when deciding on a lockdown: Would they impose a lockdown to curb the spread of the disease or would they keep businesses open and let people earn their livelihoods? (Kuhlmann et al. 2022).

The institutional setting changed significantly throughout the pandemic, leading to a substantial improvement in the distribution of regulatory powers. Specifically, the Federal Ministry of Health acquired additional authority temporarily to issue ordinances even without the explicit consent of the Laender or the Bundestag. The introduction of the “federal emergency brake” marked a pivotal moment in terms of standardization and centralization of the decision-making process and the institutional actors. This measure was actually the first measure taken on a federal level and remained in effect until the end of June 2021 when the law expired. Afterward, Germany returned to a more decentralized approach to decision-making again (Kuhlmann and Franze 2022).

Another aspect is that the public health service in Germany is generally well-structured and highly regarded for its surveillance and reporting system. Also, the country is recognized as a leader in health-related research, i.e. virology and epidemiology. These factors also contributed to a favorable context for the provision of data-driven decision-making and the formulation of policies during Covid-19 (Kuhlmann 2022). However, the level of data utilization also heavily depends on the progress of digital transformation. In Germany, the level of the digitalization process differs from state to state, and public administration to public administration, which is in direct correlation to the level of ICT-based data utilization for policy advice (Kuhlmann and Franze 2022).

In terms of the legal context, it is important to distinguish between the federal and local levels, as different laws and regulations may apply. On a federal level, the government relied on the Federal Law on the Protection against Infections (Infektionsschutzgesetz – IfSG), rather than using constitutional emergency regulations for defense or natural disasters. On a federal level, this law grants exclusive administrative power to the Laender and local governments. On a Laender level, Germany ensured the legitimacy of data-driven decisions on lockdowns, school closures, and so forth through a general clause of paragraph 28 IfSG. This gave them the right to impose restrictions on the population, such as lockdowns, shutdowns, and closures of public facilities and contact bans, but also to temporarily suspend fundamental and civil rights (Kuhlmann and Franzke 2022). This is especially relevant to the data collection. Further, it was necessary to establish legal frameworks to facilitate efficient and extensive data sharing among various levels of government and operators of critical infrastructure. By doing so, these organizations can effectively conduct comprehensive risk analyses and develop a detailed understanding of the situation during emergencies (KResCo, 2022b).

In summary, the legitimacy of data-driven decision-making was ensured mainly through the Infektionsschutzgesetz on the legal context side. The institutional context of data-driven decision-making during Covid-19 in Germany changed and evolved during the pandemic, but turned out to be a solid dynamic that ensured timely decisions. Decisions on a local and regional level ensured that containment measures could be made depending on the ever-changing data.

4.7.2 UK

In the UK, the institutional context is presented by the following statement:

> "We have already established a Data Alliance Partnership comprising the Department of Health and Social Care (DHSC) and several of its Arm's Length Bodies (ALBs), which aims to make data accessible in a timely and efficient way for legitimate purposes and within existing legislation." (Public Administration and Constitutional Affairs Committee, 2021a, p.5).

However, the question of accountability and responsibility was not clear. The question who was responsible for which decisions were not always clearly allocated. Many government bodies, departments, and ministers were involved in the data collection, management, and decision-making process (Public Administration and Constitutional Affairs Committee, 2021a). The evaluation acknowledged that

> "This Committee is clear that the data is complex and drawn from across Government and would not expect that one Department or one Minister to be responsible for producing all of the data that informs decisions" (Public Administration and Constitutional Affairs Committee, 2021a, p.28)

It is implied that lines of accountability were not always clear, as only this would legitimize the use of data for decision-making, but in reality the Cabinet Office and the Department of Health and Social Care. Some ministers denied responsibility for certain controversial decisions, such as coming out of the first lockdown or closing down hospitality sectors in the summer (Public Administration and Constitutional Affairs Committee, 2021a). However, there is a specific emergency actor, SAGE, the Scientific Advisory Board for Emergencies, an institution that had existed long before the Covid-19 pandemic and whose pre-existing structures aided in legitimized use of data and deliverance of scientific advice (Hanson et al 2021).

The main institutional and legal and policy structures that legitimized data-driven decision-making in the UK were the Covid-19 Strategy, Coronavirus Act, and Covid-19 Operations Committees, such as Covid-Operations (Covid-O). The committees convened as necessary to make operational policy decisions based on scientific advice and data (Secretary of State for Health and Social Care, 2021). However, information that was given to the Operation Committees was kept confidential. Covid-O referred to a decision-making body that could act swiftly and inform whole-of-government approaches (Public Administration and Constitutional Affairs Committee, 2021a).

Additionally, in the UK, the responsibility for managing emergencies, including prevention, response, and recovery lies with the government departments plus the acting ministers, which must be in accordance with the principle of the lead government department (Secretary of State for Health and Social Care, 2021). These agencies and their policy-owning departments often have their own specialist scientific and technical advice support which will directly supply them with the necessary data and information (Secretary of State for Health and Social Care, 2021).

In terms of the institutional context, the British parliament plays an important role in scrutinizing the decisions taken during the Covid-19 pandemic (Secretary of State for Health and Social Care, 2021). However, there is some discussion and unclarity about who is really in charge of what in the complex system of decision-making, even in the UK as a non-federal state. Data governance requires clear responsibilities in the institutional context, as well, and in the UK, it was not clear who was to be held accountable for the data that underpinned decisions (Secretary of State for Health and Social Care, 2021).

Additionally, many criticized the national-by-default approach and acknowledged that a pandemic has differing needs in different locations and does not act the same on a national level (Public Administration and Constitutional Affairs Committee, 2021a). Following the pandemic, the NHS launched a Data Strategy for Health and Social Care that built on the experiences of data governance during Covid-19. This strategy addresses the missing clear legislative framework for data-driven decision-making (Secretary of State for Health and Social Care, 2021). The shortcomings are represented in the evaluation reports, stating that for future pandemics

> "The Cabinet Office must clearly outline responsibilities for decision-making, before the Coronavirus Act is considered for renewal after 25th March 2021. This must include clear lines of accountability at the Departmental and Ministerial level, stating which Minister is accountable to Parliament for ensuring key decisions are underpinned by data, and for the data that underpins the decisions. (Paragraph 97)" (Public Administration and Constitutional Affairs Committee, 2021b, p.3).

4.7.3 Sweden

In terms of the institutional context in Sweden, it is most important to highlight the structures that led the PHA to become essentially the only player in decision-making, which encompassed the data analysis. The crisis response system, which would have been necessary to legitimize the use of data for decision-making, stated that the responsibility principle (ansvarsprincipen) applied, meaning that the authorities normally responsible for a certain domain in government, in this case, public health, would remain responsible (Andersson et al., 2021), (Regeringen, 2020).

The government never made any formal decision on the Swedish pandemic strategy but rather left all decision-making to the PHA, the expert-run agency. Politicians had no part in Covid politics. There was a Corona Commission that was tasked with overseeing the PHA's work and they began to voice concerns more loudly during the second wave of the pandemic but essentially had little influence. Prime Minister Stefan Lövfen announced on March 27, 2020, on national television: “It is the Public Health Agency that makes judgments about the spread of the virus” (Andersson et al 2021, p.5). A crisis law was introduced only in 2021 (Hanson et al., 2021) to enable the issuance of some restrictions such as the use of masks on public transport (Andersson et al., 2021). Further, the Communicable Diseases Act indicated that all measures taken by the government must be based on science and evidence (Regeringen, 2020).

There was essentially no mention of data privacy in any of the data used for this analysis. As the PHA mainly used publicly available data from Statistics Sweden and numbers of infections, and no mobile apps, this was certainly less of a concern in the use of data by the government in Sweden.

4.8 Trust

The next dimension is trust. Trust was characterized by the attributes of public perception and ‘politicization’. Those two characteristics were highly contentious and important during the Covid-19 pandemic: The pandemic has put policymaking under a novel kind of scrutiny by the public. People have lost their trust in opinion-based decision-making by governments and authorities (Huang et al. 2021).

4.8.1 Germany

Kuhlmann points to the fact that decision-making processes in Germany were not only guided by evidence, information, or knowledge but there was also a certain degree of politicization. This means that to a certain degree, science and data analysis were blamed for some of the decisions that were taken (2022).

Policymakers in Germany often took radical shifts in policy, for example by suddenly announcing lockdowns and explained the shifts by pointing to some of the data. This is to say that they justified policies by saying they were only acting upon what the data told them (Kuhlmann et al., 2022). German decision-making used quite a lot of external expertise and data providers. Some media outlets then wrote about this being an ‘expertocracy’. This ended up being discussed heavily in the media which led to a certain amount of public expectation. Consequently, public expectation led played a role in shaping the extent of political action, which could sometimes even impede the decision-making process (Kuhlmann et al., 2022).

However, the German government was open about the uncertainty of the situation and the data it had access to from the beginning. Politicians like health minister Jens Spahn repeatedly stressed that they had limited data that informed their decisions. This resulted in easier communication later on in the pandemic and also justified the rapid changing of decisions to the public (Hanson et al., 2021).

4.8.2 UK

Trust in a pandemic is essential, and trust in the data is essential. It is uncontested that if citizens trust their government, they are more likely to follow the rules and guidelines the government puts in place ((Public Administration and Constitutional Affairs Committee, 2021a).

In the UK, the first principle of the UKSA Code of Practice that underpinned the use of data in government is Trustworthiness, which includes the observance of honesty and integrity and that "statistics, data and explanatory material should be presented impartially and objectively" (Public Administration and Constitutional Affairs Committee, 2021a, p.12). This shows that the government acknowledged the importance of trust in their decision-making strategy. However, while observance of the code of practice is a statutory requirement on institutes that produce official statistics – including all government departments- this requirement does not extend to ministers. They only have to be mindful of the UKSA Code of Practice (Public Administration and Constitutional Affairs Committee, 2021a). Naturally, mindfulness can be interpreted in different ways, which is what ended up happening during the pandemic. Ministers used and utilized statistics to support their own arguments and intents, which was arguably not objective, but rather with an intent to change public opinion any which way (Public Administration and Constitutional Affairs Committee, 2021a). This clearly does not fall under the public value guidelines and is a violation of the trust reinforcement that should have happened.

In this way, the framework acknowledged an important aspect of value-based data use, trust. It became clear by looking at the three countries, that trust played a significant role in utilizing data. Public perception was hugely important during the pandemic, as citizens would only follow guidelines if they trusted the decision-makers. The national response, rather than a local one, also resulted in a lot of confusion. In the devolved states, sometimes citizens would receive two sets of recommendations, one from the UK government and then one from the state government which left people to work out what applied to them by themselves (Public Administration and Constitutional Affairs Committee, 2021a).

4.8.3 Sweden

In Sweden, there was a lot of trust in the strategy by the public and implicitly in the use of data and evidence for the decision on the strategy, which can also be explained by a generally high level of trust in public institutions by Swedish citizens (Andersson et al., 2021). This became evident in the amount of support, even though there was more public support for the strategy taken by their government in the first wave than in the second wave (Hanson et al 2021). The PHA and Anders Tegnell at its forefront kept reiterating that their decisions are always based on the available data – even though critical voices became louder towards the end of 2020 (Hanson et al., 2021, and Pashakhanlou, 2020). When media pressure built in late 2020 in response to i.e. deaths in elderly homes, the government was forced to take some actions themselves, for example by imposing face masks in public transport (Andersson et al., 2021).

However, Swedish decision-makers did not communicate uncertainties about the data. The PHA frequently stated that their recommendations were based on evidence and data and did not give room for uncertainty. This was later justified as the PHA thought admitting uncertainty would raise fear in the population (Hanson et al., 2021).

4.9 Transparency

4.9.1 Germany

The analysis revealed that there was a lack of transparency in the data-based decision-making process in Germany. Kuhlmann et al. (2022) argue that being open about the mechanics and mechanisms in which the data was shared, generated, and led to decisions was essential to ensuring transparency of the decisions. At both the Laender and the federal level, the choice of data and evidence was not sufficiently explained or justified. Actors failed to ensure the acceptance of the political measures because arguably the database was insufficient to justify certain decisions (Kuhlmann et al., 2022). This was mostly criticized by local actors who argued that there was a lot of confusion caused by these rapidly changing measures and not enough explanations for the data that underpinned them. Consequently, the local decision-makers encountered challenges in convincing the local population of the meaningfulness of measures (Kuhlmann et al., 2022). This shows the importance of ensuring transparent decision-making and the usefulness of data-driven methods to ensure the value of the decisions. Further, there was a lack of transparency on how the data providers and third-party analytics actors were selected. A study by Kuhlmann et al. (2022) revealed that there was little transparency in this process.

The timing of information was also very important, in Germany the information campaign was started very early and therefore the public was sensitized to follow the guidelines early on which led to comparably lower rates of infection (KResCo, 2022a).

4.9.2 UK

The domain of transparency was especially prominent in the data analysis. This is due to the high importance transparency plays in Covid-19 decision-making: If the public understands the data that underpins the decisions, they are more likely to follow the regulations put in place ((Public Administration and Constitutional Affairs Committee, 2021a).

However, there was very little transparency in the government and its agency's use of data for decision-making in the UK (Hanson et al., 2021). During Covid-19 governance, ministers have rarely linked the data that they use for their policies, which means that the claims they make about data cannot be verified. This is against the UK Statistics Authority Code of Practice. To improve on this, the government has put it upon itself to impose guidelines for publishing statistics. The data that underpins decisions and policies must first of all be published and hyperlinks to this data must be provided with every ministerial statement. This should be done so journalists, who will write about the data (which is the usual way the public will hear and read about new guidelines) can verify and understand the data (Public Administration and Constitutional Affairs Committee, 2021a).

In the UK, the commitment to transparency is also evident in the extensive release of scientific advice and data to the public throughout the pandemic. By the end of April 2021, a total of 684 papers and minutes from the SAGE group had been published. This was a departure from previous practices where such papers would only have been published after the emergency had concluded (Secretary of State for Health and Social Care, 2021). In this way, the UK made a conscious step to involve citizens firsthand in understanding the data that drove decisions and policies for managing decisions.

In terms of dashboards, the initial version of the Public Health England (PHE) dashboard was already published in March 2020 and has been continuously improved with additional data. PHE has also been publishing weekly Covid-19 surveillance reports since April 2020.

Further, in response to the demand for vaccine information, the government has been swift in making it available to the public. Since mid-December 2020, the start of the vaccinations in the country, weekly UK-wide data on the total number of vaccinations, as well as the breakdown between individuals under and over 80, has been published. Furthermore, the Joint Biosecurity Centre (JBC), which provides advice to ministers, primarily utilizes publicly available data. This includes testing data, information published by PHE, and data from the Office for National Statistics (ONS) (Secretary of State for Health and Social Care, 2021).

4.9.3 Sweden

In Sweden, the information campaigns started late, which meant a lot of the public remained in the dark and this led to high infection rates, especially early in the pandemic (Kuhlmann et al. 2021a). There was a website called krisinformation.se that had up-to-date information on case numbers and infection rates in the different regions. They also displayed dashboards with these statistics. In terms of reporting, the PHA introduced new reporting protocols for confirmed cases of the virus and published them on their website for open access (de Bienassis, 2022). Further, the data that was used for the modeling of scenarios was explained in these publically available reports (Folkhalsomyndigheten, 2021a).

4.10 Ethics

To analyze the ethics domain is signified by a consideration of the risks and inclusion of all data subjects that the decision is being made about.

4.10.1 Germany

There were some serious concerns about the lack of inclusion of all data subjects in the data that underpinned the decisions taken for pandemic measures in Germany. Here, transnational data were absent, which does not represent border regions and resulted in serious disadvantages in accurately representing the people living close to Poland, France, or the Czech Republic. There was no reliable data on transnational commuters, which presented problems to those authorities that had to assess the numbers of infections and other data points. Therefore, decisions on potential border closures were challenging to do, as the data was simply missing. This had serious consequences, as for example some of the commuters were personnel of health care facilities in the neighboring countries.

This was not an exclusively German problem but points to a larger European problem, where there was a lack of international comparable databases depicting the pandemic in Europe, which would have been highly useful (Kuhlmann et al 2022). The only effort in that regard was a DIVI register as a result of cooperation between the German Interdisciplinary Association for Intensive and Emergency Medicine (DIVI) and the RKI. This register showed the capacity situation of Intensive Care Units (ICUs) in Germany (OECD, 2022).

Other than that, local decision-makers had to act intuitively and often not based on accurate or representative data, or through informal communication with representatives from neighboring countries. This shows the challenges to making ethical data-driven decisions during Covid-19. However, the official documents lacked more information or consideration of the ethics characteristics.

4.10.2 UK

In terms of inclusion, one of the main complications in the UK was the disparities in the decision-making towards the devolved states of Scotland, Wales, and Northern Ireland. As discussed before, the beginning of the pandemic saw very uniform policymaking for the entirety of the UK, with a nationwide lockdown being imposed fairly soon in March 2020. However, coming out of the lockdown, disparities in policy approaches by the respective governments began. While the Chancellor of the Duchy of Lancaster was responsible for ensuring decisions were made including the devolved states, he was heavily criticized for a lack of action in the aftermath of the pandemic (Public Administration and Constitutional Affairs Committee, 2021a).

The framework indicates that data-driven decision-making must encompass data on all the data subjects. However, this was only the case to a varying degree. In an inquiry, numerous contributors highlighted a data gap when it comes to understanding the disproportionate impact of Covid-19 on individuals from Black, Asian, and Minority Ethnics (BAME) groups. In the data that was used for policymaking, this was not possible to see, as for example, death certificates do not include a category on race. While steps are being taken to include this data in the decision-making process from now on, this was an ethical disparity in the data (Public Administration and Constitutional Affairs Committee, 2021a).

In terms of consideration of risks, striking the balance between economic and social implications, such as the consequences of closing businesses versus the overtasking of hospitals and not overwhelming the NHS, was a difficult task for decision-makers (Secretary of State for Health and Social Care, 2021). Here, a problematic aspect that was highlighted is the fact that some important aspects of citizens' well-being are difficult to quantify, such as mental and emotional well-being, while economic aspects were easier to datify. Proponents of ending lockdowns in favor of the economy had an easier way of arguing their case based on data (Science and Technology Committee, 2021). However, SAGE drew on scientific advice and evidence from advisors from many different sides of the scientific community to overcome this issue (Secretary of State for Health and Social Care, 2021). While, especially at the beginning of the pandemic, it was opaque who the scientist was that provided the data and what data or papers they drew their advice from, both in SAGE and the JBC (Science and Technology Committee, 2021), they made it clear down the line that not only epidemiologists and virologists were considered for the modeling of risks, but also behavioral scientist, environmental scientists, and public health experts as well (Secretary of State for Health and Social Care, 2021).

In summary, the analysis shows that on the ethical dimension, Germany and the UK faced similar issues. Even though Germany is a federal country, due to the governance system of devolved states of Northern Ireland, Scotland, and Wales that had their own jurisdictions and disparate containment policies, there were issues for border dwellers and commuters there, as well.

4.10.3 Sweden

The consideration of risks and inclusion of all groups in Sweden was low. Arguably, the modeling and scenarios in the data analytics did account for the spread of the virus to the elderly population (Folkhalsomyndigheten, 2021; Regeringen, 2020), but these were deemed acceptable risks. Later the consequences of the lack of action, such as deaths in elderly homes and care homes, were explained away by Anders Tegnell as normal and due to other factors, such as a light influenza season the previous year (Andersson et al., 2021). In sum, some scholars have argued that the risk assessment in Sweden's data scenarios was highly controversial and even, inflexible, or wrong (Pashakhanlou, 2020).

5 Discussion

This final chapter will examine the results of the analysis, compare them to the findings of the literature review, and in doing so answer the research questions. The goal of this research was to make an important contribution to the literature by aggregating and synthesizing the existing knowledge on data-driven decision-making in government and developing a comprehensive taxonomy of the topic. Hence, the research was motivated by the questions:

1. What are the main dimensions and characteristics that define data-driven decision-making?
2. What are the drivers and barriers that should be considered when implementing data-driven decision-making?
3. How could the taxonomy be used to evaluate national data-driven decision-making in government responses to Covid-19?

While the literature review has already indicated the answer to the first question, which was aggregated in the framework, the analysis has evaluated and tested these answers. The following part will expand on how the analysis solidified the dimensions and characteristics and therefore give a conclusive answer for every dimension and its characteristics. Further, this discussion will compare and contrast the challenges and opportunities found in the literature review with the results of the analysis to answer the second question conclusively for every dimension. Finally, the results showed how the dimensions and characteristics of the framework were used to evaluate data-driven decision-making in Covid-19 responses in Germany, Sweden, and the UK. A discussion on the performance of the framework in these cases will give a conclusive answer to the final research question.

5.1 Data collection

For data collection, the framework indicated the need to assess the data access and availability, as more data does not automatically lead to better decisions, plus the need for a cohesive technical infrastructure for collection.

The results of the analysis showed that data availability was a common problem in all three countries, as the pandemic moved quickly and the data capture had to be rapid and dynamic, however, all countries had trouble setting up and continuing widespread testing. In terms of infrastructure, there were different actors responsible, and while

Germany relied on its states to take on the responsibility to manage data collection efforts, the UK managed the outbreak centrally from London and outsourced its testing to private actors, and this decidedly late which resulted in poor data availability and representativeness.

It became clear because of the results that implementing a clear infrastructure for data collection and dissemination ahead of time, that is established and where responsibilities are clearly allocated will lead to the best data available and therefore result in smooth and efficient data collection for decision-making. While the details and setups of data collection will of course depend on the area of policymaking, for their pandemic responses all three countries had already established a data collection infrastructure, but only Germany used and strengthened its existing structures. Meanwhile, the UK set up a new system outside of the public health systems which resulted in fragmented data, at the beginning even in Excel spreadsheets, that was provided to decision-makers. In Sweden, there was even very little effort made to set up a data collection system by the PHA. The lack of representative data in the end directly influenced the choice of pandemic strategy.

To sum up, regarding the drivers and challenges of data collection, the results indicate that strong leadership and having pre-existing data collection structures will result in higher data availability and representativeness for decision-making. It seems, adjacent to the literature review indicated that more data did, in fact, lead to better decision-making, especially during the first wave of the pandemic. Further, the driver of a cohesive infrastructure also indicated in the results that having pre-existing systems will lead to efficient data collection, certainly an implication for the implementation of data-driven decision-making that adds to the infrastructure characteristic in the data collection dimension.

5.2 Data quality

In terms of Data Quality, the framework suggested the need for accuracy in the data to erase uncertainties, which could be achieved through the expansion of databases, better data visualization, and more in-depth analytics, always while preserving citizens' data privacy. Further reliability and validity of indicators need to be assured, as faulty data results in faulty decisions. Finally, the framework indicated that the representativeness of data is important for quality, as there is a danger that incomplete data and data gaps will be ignored because of false confidence in Big Data.

The analysis showed a few common themes for all three countries that show the drivers and barriers of data-driven decision-making in terms of data quality. First, there was a timeliness versus data quality trade-off experienced by both Germany and the UK. The urgency of the pandemic demanded quick decisions, but often there were limited testing capabilities to provide accurate data, especially at the beginning of the pandemic. In the UK especially, there were difficulties transferring the data and integrating it into the existing systems. This resulted in data gaps concerning the virus's spread and impact. In Sweden, the low quality of the data concerned the reliance on data sources from China and foreign recommendations. This resulted in the lack of mitigating action against the virus and represented the danger of false confidence in Big Data quite well.

The results showed that data quality is difficult to achieve, but the characteristics are highly relevant to the outcomes of decision-making. In terms of all three characteristics, but mainly representativeness, is that it was also important to detect where the data comes from, as seen in the Swedish case. However, this also showed how important this aspect is, as the Swedish decision not to take action based on faulty data, had a widespread impact on the people in Sweden. What can further be added to the reliability and validity characteristic is that not only faulty data results in faulty decisions but also un-timely and late data, as became obvious in the rapidly developing pandemic. Further, the danger of data gaps, as discussed in the framework cannot be overstated, as can be seen by the UK's example where for a long time no lockdowns were imposed because of data gaps.

5.3 Skills and competencies

The framework indicated skills and competencies as characterized by the changing role of decision-makers and their capabilities to adapt, the collaboration of stakeholders with different skills, and the data literacy of the actors involved.

The results showed that in terms of collaboration, Germany had a more collaborative decision-making structure involving various actors at different levels of government and relying on external expertise for epidemiological and virological expertise, and setting up task forces for interdisciplinary knowledge. However, they faced challenges in dealing with information overload, requiring a high level of informational capacity on the administrative-political side. The UK had a centralized decision-making structure where key decisions were made by the center of government but required collaboration with local leaders. The UK relied heavily on SAGE and its subcommittees for data analysis and informed decision-making, an entity with long-standing expertise in data analysis and provision for emergencies. They also collaborated with private actors for data gathering and analysis, however, this led to difficulties and time delays. Sweden had a more centralized governance structure, with decision-making largely delegated to the Public Health Agency and its chief epidemiologist, and little collaboration. This led to criticisms later on.

This showed the importance of the collaboration aspect of the framework: Both Germany and the UK brought in a lot of outside expertise, Germany through consultations with experts, and the UK through the government's close collaboration with science and academic institutions. The results showed that data literacy and understanding by leadership is essential for even setting up the necessary structures for data provision and dealing with information overload, a discussion that the framework included, as well. The role of private players in the decision-making process needs to be assessed closely, even though the results did not indicate specifics regarding the privacy trade-off, rather it was implied that it must be clear where the data is coming from, and this be made transparent.

5.4 Data analytics application

The next domain is the use of data and data analytics applications. This was defined in the framework by the data infrastructure, the interpretation of the data, and the operational improvement and modeling. The results regarding Germany mainly indicated that its pre-existing data infrastructure DEMIS allowed the country to gather data centrally and give access to the relevant decision-makers, but also for data providers to load their data into the system. There was no indication in the reports about the scenario modeling in Germany. In the UK, the problems with allocating responsibilities are also related to the data analytics application. They tried updating their systems last minute which resulted in fragmentation. In the UK, decision-makers were clear to say they only based their decisions on the data modeling which resulted in a reduction of the R number from March 2020 until October 2020 by around 0.3-0.6, showing the opportunity and capability of data analytics application for decision-making. In Sweden, the data modeling was described the most, and specific scenarios were calculated and made publicly available. However, this made faults with the interpretation of the data obvious.

The results of the analysis show again that having systems and structures in place before a crisis where rapid action and decision-making are required, and also applies to data infrastructure. Germany with its DEMIS system worked efficiently with all relevant stakeholders attached. Concerning the operational capabilities, while not a lot of detailed data was available on the inner workings of the analysts in each country, also showed how closely the characteristic relates to the interpretation of the data. Sweden is an excellent case of how interpretation can change decision-making and that data is not value-neutral and this is certainly a barrier in data-driven decision-making.

5.5 Use of automated and AI decision-making

The use of automated decision-making received very little coding in the analysis. It seems that the use of AI in decision-making is widely discussed in the theory and academic literature, but it has not made it to the official government reports or evaluations. While AI was certainly used in the pandemic response, this was done for operational purposes like healthcare rather than decision-making. However, the framework already indicated that this is a hot topic in the research but has seen fewer real-life use cases at this point. For Covid responses, this was not relevant enough yet. Further research however into data-driven decision-making could uncover more in this dimension and the fact that the results showed that the use of AI will be relevant for future responses shows that it is a relevant dimension in the framework.

5.6 Data Sharing

The framework uncovered the domain of data sharing as an essential enabler, but also a challenging point to data-driven decision-making. Data sharing was an equally essential point in the results. Achieving collaboration and interoperable sharing of the relevant data was problematic and complex for all three countries.

The results showed that major problems arose in terms of data sharing between national, sub-national, regional, and local levels. The results focused on data silos and lacking infrastructure in all three countries. Even though Germany is a federal country and had a very decentralized approach, it managed to get all data collectors and decision-makers to share data across silos. The UK relied on its existing culture of collaboration with science through a range of data-sharing agreements. Sweden had fewer issues regarding interoperability, as decision-making was essentially done by one entity, the PHA, and there was very limited testing in the country.

Some of the prior dimensions, including the data and data collection infrastructures had already uncovered the challenges and barriers with data silos and lacking interoperability between the relevant stakeholders, however, this dimension focused specifically on the stakeholders and how to overcome interoperability issues. The results show how complex the task of data sharing is, as all countries had to take steps to incentivize stakeholders to share their data. The case of Sweden was again an outlier, as there was little data to be shared, this was mostly relevant from the regional level towards the PHA. This shows that sometimes data-sharing can involve many stakeholders that need to collaborate where pre-existing structures are necessary that need to be financially incentivized, but it can also be relevant to assess data sharing on a smaller scale. This is another advantage of the framework, due to its detailed nature of many characteristics and 10 total dimensions, it lets researchers and implementors of data-driven decision-making apply it to many cases. This can also be seen with the data sharing dimension, which uncovered details about the process in both federal and unitary states and the challenges of data sharing for them.

5.7 Legitimacy

Legitimacy was characterized by institutional and legal context and support, plus the data privacy consideration, in the framework. The drivers here were that a clear institutional and legal mandate will enable legitimate use of data for decision-making, but also that sometimes the need to preserve citizens' data privacy can be a barrier to data-driven decision-making.

While all three countries acted upon different laws that enabled them to make decisions, this was never exclusively data centered. In terms of institutional support, the German multi-level approach appeared to generate smoother pandemic management. In the UK, responsibilities were not always clearly allocated and lines of accountability were blurry, however, the Coronavirus Act legitimized the use of data for decision-making. The results also showed that the domain stakeholders, meaning who was involved in the decision-making process are very relevant: Both in Germany and the UK many actors were involved in the decision-making process, and there was a lot of collaboration with data providers and institutions. While this was also subject to politicization – a characteristic that certainly is relevant in the framework- this did legitimize the decision-making process. In Sweden, on the other hand, the decision-making was essentially up to one agency, and if one were to be critical, it could even be argued it was up to one man, Anders Tegnell, the chief epidemiologist. His was the final say on what data to use and what data to base his decisions on to not impose any restrictions but rather give loose recommendations. This has become evident in the legitimacy and data use domains of the framework. Therefore, these domains and their characteristics are highly relevant. The case of Sweden solidifies the importance of the dimension of legitimacy but also begs the question of a clear institutional mandate, as was the case in Sweden, where the government structure enables the power of government agencies, such as the PHA, is enough to ensure good decision-making.

5.8 Transparency

The framework identified the reporting and making information and data and open data publicly available, plus the timing of this as the drivers and barriers for transparency.

Germany lacked transparency in the data-based decision-making process, with an insufficient explanation of data choices and confusion caused by rapidly changing measures. The UK made efforts to improve transparency, publishing data, and scientific advice, providing dashboards and vaccination information, and utilizing publicly available data. Sweden had a late start in information campaigns but provided up-to-date information and explanations of data used for modeling scenarios.

These results show that making data publicly available makes a difference: In Germany, people had difficulties understanding the rapid changing of containment measures, especially as they differed from region to region. However, an early extensive information campaign and open data dashboards, let people understand the type of data that was used at least. In the UK, evaluation let us know that ministerial statements would have needed detailed links to the data that underpinned the decisions. Sweden published the scenario modeling that dictated their overall strategy but failed to begin an information campaign with regular reporting, meaning many citizens remained in the dark about high infection rates which led to criticism later on. Generally speaking, transparency was highlighted many times in the evaluation reports as a necessary factor for data strategies during Covid and should certainly be a key point in any implementation of data-driven decision-making.

5.9 Trust

The domain of trust was characterized by public perception and politicization of the data. The framework identified that the use of data and Big Data can lead to more public support for decisions, but also saw that data could be used for pre-existing political agendas as the barriers and opportunities of data-driven decision-making regarding trust.

The results showed that Germany faced challenges in trust due to public perception and politicization of decision-making, while the UK experienced violations of trust through the politicized use of statistics by ministers. Sweden had a higher level of trust in the strategy and data use, although uncertainties about the data were not communicated. It was interesting to see that only in Germany did lack of data and uncertainties due to the available data being communicated to the public. Both in the UK and Sweden decision-makers simply insisted on having reliable data.

However, public support also changed a lot in all three countries throughout the overall time of the pandemic and so this characteristic should be discussed in light of a specific time frame or in stages of time. Generally, it became clear that trust in the data that underpinned decisions is essential for citizens to follow the decisions, in this case, rules and recommendations by the government to mitigate the spread of the virus and therefore this should be seen as an essential driver for data-driven decision-making implementation.

5.10 Ethics

The domain of ethics was characterized by several drivers and barriers: The responsibility of stakeholders was to understand the power dynamics shift, the consideration of risks that data can also lead to wrong decisions, and the inclusion of all data subjects into the data that underpinned the decision-making process.

The results indicated mainly concerns about the inclusiveness characteristic. In Germany, there were concerns about the lack of inclusion of all data subjects, such as the digital divide in mobile phone tracking and the absence of transnational data, which affected decision-making accuracy, especially regarding border regions. The UK faced disparities in decision-making for devolved states and a data gap in understanding the impact on minority ethnic groups. Striking a balance between economic and social implications was challenging, as quantifying well-being and considering non-economic aspects was difficult and this risk was taken into account. Sweden faced criticism for its risk assessment and lack of action, particularly regarding the elderly population in care homes which showed a lack of understanding of the responsibility of the government to use the data for all. The characteristics of ethics were highly relevant for the case study of Covid-19 decision-making altogether. Further empirical research could indicate more results regarding how risks are taken into account during the data analysis and provisions, as well.

5.11 Overall performance of the framework

Overall, the framework and the analysis gave a comprehensive picture of the barriers and drivers of data-driven decision-making during Covid-19 in Germany, Sweden, and the UK. The analysis through the lens of the framework solidified the choice of dimensions and characteristics of the framework and answered the research question of how the framework could be used to evaluate data-driven decision-making in government responses to Covid-19.

The view through the dimensions allows the researcher and implementors to detect to understand all aspects of the structure that is necessary, the stakeholders that are involved, including citizens through the legitimacy, trust, transparency, and ethics dimensions, that governments need to keep in mind. While during the coding, some data could correspond to several dimensions, one of the strong points of the framework is that it defined its characteristics quite narrowly. Looking for the characteristics in the data was simple and easily attributable to the dimensions then. The challenges and opportunities in the framework for every characteristic could be found in the analysis and in the case of Covid-19 decision-making overall.

There was a lot of data and reports available for Germany and the UK, but fewer for Sweden, which could be seen by the length of text for every country. However, the framework was still applicable which shows its usability and strengths. These three countries had very different Covid-19 responses but the framework allowed for distinct comparisons and uncovered the common challenges and opportunities of data-driven responses, but also allowing the differences to reflect back on the debates in the framework. While not every dimension or characteristic produced the same amount of codes, it was overall similar which shows that every dimension was necessary and important to have. The discussion has highlighted the specific issue with the automated and AI decision-making dimension which was not as relevant for the cases used at this point but will become essential in the future and would be essential with access to primary data, in this case, to uncover why AI has not been used to a large extent for Covid-19 responses yet.

5.12 Limitations

Apart from the contribution this paper made to the literature on data-driven decision-making, it is also important to clarify that this study faced some limitations. First, consolidating the existing research into dimensions and categories naturally depends also to some degree on the researcher's understanding and choices when faced with a large number of studies and may come with a higher risk of bias. While this study focused on a narrow selection of articles to mitigate this problem to some extent, this should still be kept in mind. It is recommended to pursue further research into individual domains.

In addition to this, one must bear in mind that this is an exploratory research study that did not aim or cannot provide fully conclusive results. This was meant as a starting point to give a comprehensive picture of the current state of literature and see how applicable the deducted framework could be in a case study. While the study analyzed three different government approaches to data-driven decision-making through the lens of the framework, applying it to further cases outside of crisis response may shed light on more permanent decision-making structures. Further research could expand the framework, adding additional characteristics or focusing on only certain domains and going into depth on exploring those characteristics in separate literature reviews, thus expanding the framework further. In terms of implications for future research, this framework could be applied in more detail through interview data with those stakeholders that are directly involved in government decision-making processes, rather than having to rely on reports and documents provided by the institutions. While this was a comprehensive and goal-oriented way to test the framework for this study, being able to ask specific questions on the dimensions of the framework could highlight the enablers and challenges of data-driven decision-making in even more detail.

6 Conclusion

Finally, this thesis developed a comprehensive taxonomy for data-driven decision-making in government. It provided a state-of-the-art picture of the main drivers, building blocks, and barriers on the topic of data-driven decision-making to guide implementation, but also motivate and facilitate further research in this direction and into the individual dimensions.

To do so, a taxonomy was developed based on a systematic literature review that can guide decision makers in government, public administration personnel and researchers on how to develop a decision-making process based on data. This framework was tested for soundness by applying it to three cases of Covid-19 policymaking in different countries, these being Germany, the UK and Sweden. This has shown that the framework is usable and includes the necessary categories to frame data-driven decision-making initiatives. The literature review already indicated the main dimensions and characteristics that define data-driven decision-making, but the evaluation of applying the framework to the cases solidified the dimensions and characteristics and gave a conclusive answer to this research question. The discussion compared and contrasted the challenges and opportunities of government data-driven decision-making to those found in the literature review and was able to give a comprehensive answer for every dimension. The analysis also showed how the framework of dimensions and characteristics can be applied to evaluate national data-driven decision-making in government responses to Covid-19.

This thesis adds to the research on data-driven public sector by focusing on the concept of data-driven decision-making and conceptualizing the existing research for the implementation of such initiatives. While research on this topic exists , this thesis aggregated the existing, up-to-date knowledge into an applicable framework. In terms of implications for further research, further cases of data-driven decision-making could be analyzed through the framework and the implications of this research used to expand the framework. Additionally, for example a public value lens could be used to highlight the citizen's perspective, by only picking certain dimensions of the framework, i.e. transparency, trust, legitimacy, and ethics.

This research could also be built upon to investigate the use of data for Covid-19 responses further. The results of the analysis make some relevant points for pandemic and crisis management that if contextualized by research into this field could be used to inform future pandemic governance. Here an interesting point is that the results reflect the success of pandemic management. While the success of

Covid-19 governance is very complex to define and quantify, and this paper does not attempt to do so, nor is it necessary to answer the research questions, the fact that the UK and Sweden had two of the worst excess-mortality outcomes does reflect on the decision-making. This also implies the need to compare and contrast different actors' experiences when it comes to data-driven decision-making. According to researchers, had the UK adopted Sweden's approach, the mortality would have doubled, had Sweden adopted the UK's approach, the mortality would have halved (Mishra et al., 2021). Additionally, the topic in the realm of health will remain interesting and relevant throughout the launch of the upcoming EU Health Data Space, which will certainly affect the decision-making processes in terms of data collection and data availability in the health domain (OECD, 2022). Once health records and patient registries are fully digital, genomics data are more widely available for secondary use of data, meaning for health research and policymaking, decision-making in this policy domain will change more and more towards data-driven.

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I hereby declare that, to the best of my knowledge and belief, this thesis titled *Unveiling a Comprehensive Taxonomy for Data-Driven Decision-Making in Government: Assessing the Use of Data for Covid-19 Responses* is my own, independent work. I confirm that each significant contribution to and quotation in this thesis that originates from the work or works of others is indicated by proper use of citation and references; this also holds for tables and graphical works.

Münster, 06.06.2023

Sabrina Johanna Waizmann

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