# Mobility Data and Non-Pharmaceutical Interventions During COVID-19 – A Literature Review

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# Acknowledgements

When COVID-19 was declared a pandemic a little over a year ago few people would have guessed the extend of which it has affected all our lives since then. The motivation for embarking on this journey arose from the wish to achieve knowledge that can help us when the next pandemic strikes. Hopefully, by then we will be better prepared as a result of the research performed on the area.

I would like to especially thank my supervisor, Mette Skov, for competent guidance, motivation, interesting discussions and for always being helpful during the process.

Enjoy.

- Rolf Mahon

# Abstract

**Title:** Mobility Data and Non-Pharmaceutical Interventions During Covid-19 – A Literature Review

**Aim:** The literature review researched the use of mobility data generated from smartphone application which were aggregated and made available by big tech companies during the COVID-19 pandemic. The purpose of doing so was to create a synthesis of knowledge based on the copious amounts of research made on COVID-19 and understand a dimension of the digital tools used during the pandemic.

**Method:** The methodology was a grounded theory approach which deployed a systematic literature search and a constant comparison analysis with coding of the texts in three phases. The literature search provided 19 articles from three databases (Scopus, ACM, Web of Science) on the topic of COVID-19, non-pharmaceutical interventions and mobility data passively collected from smartphone applications.

**Findings:** The analysis identified data sources of mobility data and the metrics used to measure mobility changes in response to NPIs and its effect on the COVID-19 infection. Further it elucidated the different geographical contexts where mobility data were applied.

**Conclusion:** In conclusion, the big data approach of using mobility data to understand the relationship between non-pharmaceutical interventions and transmission of COVID-19 from person-to-person can produce insights and actionable knowledge on multiple geographical scale. There are, however, fundamental issues with data privacy, dataset transparency and a lack of consensus and standardization of the research. While some findings were observed across studies, certain findings were in direct contradiction with each other.

# Content

## List of Abbreviations

- Non-Pharmaceutical Intervention (NPI)
- Point of Interest (POI)
- Census Block Group (CBG)
- General Data Proctection Regulation (GDPR)
- World Health Organization (WHO)

# Mobility Data and Non-Pharmaceutical Interventions During Covid-19

A Literature Review

## Introduction

A year after being classified as a pandemic the coronavirus disease (COVID-19) has infected more than 110 million people, cost over 2.6 million lives globally (Dong et al., 2020), caused untold economic damage and is responsible for, perhaps, the largest disruption of life in newer times. The disease, which is caused by the SARS-CoV-2 virus, mainly spreads from person-to-person when people are in close proximity to one another (WHO, 2020). The spread of diseases characterized by person-to-person transmission are greatly impacted by human mobility and social interactions (Chen et al., 2014, p. 5-6). Studying people's movement in space and time goes as far back as the 1950's, but the scholarly interest in human mobility has especially increased during the last couple of decades due to the data on human movement/travel that mobile phones has made available (Barbosa et al., 2018, p. 5). The digital evolution from mobile phone to internet enabled smartphone is only recent and Goodchild's (2007) formulations of humans as a sensory network seems even more accurate today, due to the ongoing increase in penetration rate and sensor capabilities of the internet-enabled mobile devices that we carry around in our daily lives. This recent emergence of personal mobile access to the internet is considered the greatest recent revolution for information and communication technology (ICT) (Aguiléra, 2019, p. 2). The vast amounts of data that is generated from smartphones daily can be classified as 'big data' and Cheng et al. (2018) describe mobile big data as an underexploited goldmine when it comes to location data. Mobile location data however is not impervious to issues such as bias (Coston et al., 2021) and privacy concerns (Huang & Gartner, 2018; Zickuhr, 2013). Data from our smartphones has the potential for identifying the human mechanism that perpetuates the COVID-19 pandemic, how to effectively intervene and answering the questions of the public debate on the merits of deploying non-pharmaceutical interventions (NPI) as preventive measures. When COVID-19 was declared a global pandemic by the World Health Organization (WHO) on 11th March 2020 (World Health Organization, 2020) an estimated 3.6 billion smartphones were in use globally (Deloitte, 2019). The thesis will be a literature review that narrows in on location data generated from human interaction with the before mentioned 3.6 billion smartphones and the scientific discoveries and advances that have been made during the COVID-19 pandemic by analyzing these data. The focus will be on research that uses spatiotemporal data in context of the COVID-19 pandemic. It will contain an analysis and synthesis of a carefully selected body of literature to elucidate trends, patterns and themes in the research area as a basis for discussing implications of the selected literature and using mobile devices for studying mobility and infectious diseases during COVID-19.

## Delimiting the Research

The purpose of this chapter is to present my rationale for conducting the literature review and provide the reader with the necessary frame of context for understanding that smartphone mobility data, human behaviors and pandemic characteristics are interconnected. I will do this by demonstrating the precedents of research in human mobility, how phones have been used for this previously and why it is relevant in context of COVID-19. The intention of doing so is also delimiting the research area and explaining the rationale I used to arrive at the body of literature that will be examined.

### Coronavirus Disease and Non-pharmaceutical interventions

> *"A pandemic is defined as a global epidemic caused by a new influenza virus to which there is little or no pre-existing immunity in the human population" (World Health Organization, 2019 p. 3).*

In the event of a pandemics where there is no available vaccine, 'non-pharmaceutical interventions' (NPIs) are the only set of pandemic countermeasures that are readily available at all times and in all countries (World Health Organization, 2019, p. 1). NPIs are often based on what is also called population prevention strategies that affect the entire population or large groups of it (Wolfram & Fuchs, 2008, p. 1122). Early implementation of such interventions can be imperative for reducing lives lost and the economic damage (Smith, 2006, p. 3120). The purpose of implementing NPIs is reducing the disease transmission and morbidity by delaying the introduction of the virus into new populations and delaying the transmission rate overall by introducing personal, environmental, social and travel measures (World Health Organization, 2019, p. 1). This is where the term 'flattening the curve' stems from, which implies keeping the contamination rate at a constant manageable level. Mitigating the impact of a pandemic in this way is best achieved by reducing interactions and contact between infected and uninfected individuals even though NPIs also include other measures that slow the spread of a virus (World Health Organization, 2019, pp. 4, 8). The World Health Organization (2019) suggests 15 NPI measures which include: **personal protective measures** (hand hygiene, respiratory etiquette, face masks), **environmental measures** (surface and object cleaning, other environmental measures (increased ventilation)), **social distancing measures** (contact tracing, isolation of sick individuals, quarantining of exposed individuals, school measures and closure, workplace measures and closure, avoiding crowds), **travel-related measures** (travel advice, entry and exit screening, internal travel restriction, border closure) (World Health Organization, 2019, pp. 13-18). NPIs work best when performed proactively which is difficult, since doing so requires understanding of the flow of goods, services and people during an emergency (Smith, 2006, p. 3121). Due to the incubation period (time from contamination to symptoms) of COVID-19 being on average 5-7 days, and up to 14 days, the effect of NPIs on Covid-19 cases and transmission rates are impossible to observe in real-time (World Health Organization, 2020c). (Snoeijer et al., 2020 p. 15). The two-week delay from implementation of an NPI to a potential effect showing in statistics makes it necessary to understand if NPIs make people change their behavior when they are implemented. If the population does not comply with restrictions the effect is likely insufficient. This is where measuring mobility becomes interesting in understanding if further intervention or change in strategy is required. According to Snoeijer et al. (2020) "(…) assessing the effect of implementing

and releasing the NPIs in a single country or area on the corresponding mobility will give a good pre-indication of the effectiveness of those measures on the COVID-19 spread." (Snoeijer et al., 2020 p. 15). Better understanding the effect of the communication involved in large scale NPIs can benefit from population mobility data collected by large private companies (Buckee et al., 2020). I will go into further detail about the ICTs used for these aggregating mobility data in the next chapter.
In summary NPIs attempt to encourage preventive health behaviors in a population and discourage behaviors that perpetuate the spread of a disease. NPIs are public health interventions and rely on compliance from the population with the restriction and recommendation they communicate. But what determinates if people choose to follow directives? This requires further knowledge of the mechanism controlling health behavior in individuals.

A crisis can be perceived as a precursor to a disaster and in context of COVID-19 avoiding a crisis evolving into a disaster is linked to maintaining enough control over the situation so that hospital care capacities are not exceeded (Ogie & Verstaevel, 2020, p. 8). Hutton (2012) further states that disasters are not entirely natural but rather "(…) a product of the interface between hazards and human activity." (Hutton, 2012, p. 1). According to Siepmann (2008), people's behavioral patterns are a leading course of dead and disease and, in a public health perspective, travel-related behaviors are a part of that pattern (Siepmann, 2008 pp. 516-517). Early interventions to pandemics can be imperative in the reduction of lost lives and economic damage but are often implemented based on incomplete information (Smith, 2006, p. 3120). According to Smith (2006) proactive decision-making requires understanding of the flow of goods, services and people during an emergency (Smith, 2006, p. 3121). Yet epidemic models predicting and assessing risk are not always accounting for human behavior as a variable (Ferguson, 2007, p. 733) even though human behavior is a fundamental variable in increasing/decreasing the person-to-person transmission happening through social contact (Raude et al., 2020, p. 2). Gielen & Sleet (2003) claim that most failed interventions happen due to lack of knowledge of the determinants of behavior and not applying health behavior theory to the interventions process (Gielen & Sleet, 2003, p. 66).

But on what basis do people regulate their behavior in a pandemic event? According to Ferrer & Klein (2015) "Risk perceptions – or an individual's perceived susceptibility to a threat – are a key component of many health behavior change theories" (Ferrer & Klein, 2015, p. 85). The fundamental premise in this branch of behavior change theory is that people will change/adjust their behavior according to a perceived risk to reduce it (Ferguson, 2007, p. 733). Meanwhile Sheeran et al. (2014) provides a more exhaustive explanation of preventive health behavior in individuals and attributes it to increased risk appraisal and coping appraisal. They support their claims based on a meta-analysis of empirical evidence proving correlation between risk appraisal and its determining factor for people's actions and decision-making (Sheeran et al., 2014, p. 511). Risk appraisal covers the variables of "risk perceptions, anticipatory emotions (e.g., fear, worry), anticipated emotions (e.g., regret, guilt), and perceived severity." (Sheeran et al., 2014, p. 511). While coping appraisal consists of "response efficacy (perceptions of how much the recommended behavior is likely to alleviate the hazard), (…) self-efficacy (the person's confidence in their ability to execute the recommended behavior), (…) response costs (the person's perceptions of the disadvantages of, or barriers to, undertaking the behavior)" (Sheeran et al.,2014, p. 514).

Changing public health behavior is more likely to be achieved when interventions successfully make people internalize one or more of: "(…) (a) believe they are at risk, (b) feel worried about the threat, (c) feel guilty if they do not act, or (d) believe that the harm would be severe (…)" (Sheeran et al. 2014, p. 534). Preventive health behaviors have been observed to increase with the increasing prevalence of a disease but perceived risk and therefore health behaviors decline over time as well (Raude et al., 2019, p. 189 & 192). This phenomenon is attributed to risk habituation which is the defined as "The process by which there is a decrease in behavioral response (orienting response) to a stimulus that is repeatedly presented over time." (Cohen, 2018, p. 1631).

Without the necessary knowledge managing a pandemic event, experts and politicians setting regulations rely on educated guesses and judgements, which can be fallible. Understanding the determinants for behavior for an entire population, or statical significant size population, requires other methods and this is where passive data from smartphones, among other things, becomes an interesting tool.

## Emergence of the Smartphone and the Paradigm Shift in Mobile Sensing

One of the principles in disaster informatics is that people generate data in their daily interaction with ICTs and using that data can be helpful for responding to disasters and cope with uncertainties related to disaster events (Palen & Anderson, 2016). In their review on disaster informatics Ogie & Verstaevel (2020) define the term as:

> *"Disaster informatics is the study of the design, development and use of information and communication technologies by people and organisations to generate, gather, process, store, and distribute the information required for improving decisions and actions in the preparation, mitigation, response, and recovery phases of disasters*." (Ogie & Verstaevel, 2020, p. 8).

Two decades ago, White & Wells (2002) suggested that the increasing number of phones created an opportunity to extract anonymous location data that could "asses traveler's behavior either under normal conditions or following a strategic diversion plan" (White & Wells, 2002). Six years later, González et al. (2008) used Call Detail Records (CDR) from 100.000 phone users to statistically prove the probability of an individual being in a specific location and demonstrated the potential of studying human mobility with big datasets from mobile phones. Traditionally, studies on human mobility were concerned with statistical quantification of human travel by analyzing the trajectories of individuals in their daily lives. The purpose of doing so can be described as "(…) understanding the basic laws governing human motion (…)" (González et al., 2008, p. 779), understanding the dynamics and statistics of human travel and how it affects spatiotemporal phenomena (Brockmann et al., 2006) or more specifically predicting the spread of disease by understanding the mobility of individuals (Song, Qu, et al., 2010). Prior methods for studying human mobility have examined the dispersal of bank notes (Brockmann et al., 2006) but the area mostly gravitated towards using mobile devices as they grow in ubiquity. Earlier studies that adopted mobile device location data has used CDR (De Montjoye et al., 2013; González et al., 2008; Isaacman et al., 2012; Lu et al., 2013; Pappalardo et al., 2015; Song, Koren, et al., 2010; Song, Qu, et al., 2010). CDR are logs of phone calls and short message services (SMS) originally kept by telecommunication providers for billing purposes (Zhao et al., 2016) and just a decade ago it was considered "(…) the most detailed information on human mobility across a large segment of the population (…)" (Song et al., 2010, p. 1019). However, using CDR as a method has a few technological limitations. Firstly, it is dependent on users sending or receiving calls and text messages via cell tower and cannot provide location information if the user is not active (Cheng et al., 2018; Zhao et al., 2016, p. 1759). Secondly, with the emergence of 'over the top' (OTT) service providers and mobile applications (app), much of the traditional telecommunication traffic has moved to alternative services via the internet (Sujata et al., 2015). Thirdly, it only provides an approximate location of the user within the range of the cell tower that receives the call or text message (Barbosa et al., 2018). Just as analyzing the trajectories of banknotes has grown outdated due to physical money being outsourced to better alternatives, such as credit cards and mobile payment, CDR is being surpassed by newer technologies. This is mainly due to a combination of mobile internet access which the emergence of smartphones has made a commercially available commodity and these devices carrying embedded global positioning systems (GPS).

The swift adoption and increasing ubiquity, computing power and sophistication of embedded sensors has enabled the smartphone to open the door to a whole new paradigm of sensing. Guo et al. (2015) defines Mobile Crowd Sensing and Computing (MCSC) as - "a new sensing paradigm that empowers ordinary citizens to contribute data sensed or generated from their mobile devices and aggregates and fuses the data in the cloud for crowd intelligence extraction and human- centric service delivery." (Guo et al., 2015, p. 2). All internet-enabled mobile devices and vehicles are part of this 'internet of things' (IOT) that generate sensors data on a societal scale (Ganti et al., 2011, p. 32). MCSC also extend beyond the smartphone (e.g. wearables, smart vehicles and internet enabled user-companion devices in general), but in this thesis I will focus on the smartphone since it is the most widespread technology and provides unprecedented spatiotemporal coverage of its users (Guo et al., 2015, p. 4). MCSC differs from Burke et al's (2006) participatory sensing since it includes implicit 'participation' data generated by the user. Implicit data is also sometimes referred to as opportunistic or passive data sensing and autonomous in nature, requires minimal involvement and no explicit action from the user (Ganti et al., 2011, p. 32). It is this specific type of data, aggregated from smartphone users, which my thesis will focus on.

The introduction of the smartphone, which combined mobile computing, internet access and traditional telecommunication, provides additional opportunities to collect mobility data that is not limited in the same way CDR are. This is not to say older methods are obsolete but rather that the emergence and proliferation of mobile internet access surpassed the data generation capabilities and technological limitations of the older methods. Barbosa et al. (2018) makes a distinction between CDR and the newer iteration of ICT enabled data generation, that internet access on smartphones provide, and contribute it with the "(…) advantage of having more contextual information associated with the geographical positions and the users, enabling the study of mobility in a broader context (Barbosa et al., 2018, p. 12). In this thesis I will focus on the smartphone technology and mobility data generated by internet-based smartphone applications during COVID-19.

Human mobility studies in general contributes to the area with a range of applications and a consensus exists on its usefulness in understanding and predicting infectious disease phenomena (Barbosa et al., 2018; Brockmann et al., 2006; González et al., 2008; Jurdak et al., 2015; Perchoux et al., 2013; Song, Koren, et al., 2010; Song, Qu, et al., 2010; Yan et al., 2013). According to Merler & Ajelli (2010) it is well established that epidemics are impacted by the spatial dynamics of a population. A notion that Brockmann et al. (2006) formulated as "(…) Human travel, for example, is responsible for the geographical spread of human infectious disease." (Brockmann et al., 2006, p. 462). Modelling and predicting the spatiotemporal spread of disease by analyzing human mobility can be a useful instrument for developing effective and strategic non-pharmaceutical interventions (NPI) but it also requires the right methods and tools (Chen et al., 2014, p. 3). The emergence of novel infectious diseases have shown to rise significantly over time (Jones et al., 2008). With the increasing occurrence of pandemics it is a question of when the next one will happen rather than if it will happen (Ayres, 2020, s. 583; Morens et al., 2020, s. 1). This has created "(…) an increasing need for effective, evidence-based surveillance, early detection, and decision-making methods" (Scarpino et al., 2012, p. 1). Since smartphones are likely the largest and most advanced dynamic sensor network that currently exists on the planet, it makes the technology a prime candidate for understanding the spatiotemporal patterns that are important to identifying effective preventive interventions for disease spread (Chen et al., 2014). The smartphone is more than just a device - it is also a phenomenon on its own (Klemens, 2014, p. 3). A phenomenon which has enabled measurement, analysis and modeling of individual behaviors and even changed our way of life due to the implications to practices such as travelling (Aguiléra, 2019, p. 1-2). The current metaparadigm of technological revolution is an endeavor of collecting data with ICT (e.g. the smartphone) and transforming the information with algorithms to automate the processes of producing actionable knowledge (Hilbert, 2020, p. 193). For knowledge to be 'actionable' it must transcend descriptiveness and facilitate predictions by extracting generalizable data (Dhar, 2013, p. 64). The current state of the data landscape is also referred to as 'big data' which is a "(…) general term for the massive amount of digital data being collected from all sorts of sources." (Kim et al., 2014, p. 78). Big data is at the core of the thesis which will revolve around "behaviors recorded or converted into computational systems" (Cao, 2010, p. 3069). Specifically, the behaviors related to movement, travel, and mobility in general, that are recorded by smartphones. The question that remains is if the data we passively generate in our daily lives are applicable for creating knowledge on an event of COVID-19's magnitude and if mobile sensing of mobility can deliver on the promises made about its usefulness. How mature is the approach when the stakes are as high as with the case of COVID-19?

Boyd & Crawford (2012) suggest that we should question the implications of the tools we use - “As scholars who are invested in the production of knowledge, such interrogations are an essential component of what we do.” (Boyd & Crawford, 2012, p. 675). A challenge for big data, and its effect on public matters, is that few has the expertise to analyze it (Boyd & Crawford, 2012, p. 675). As pointed out by Ewing (2011) this comes with the danger of big data being misused “as a rhetorical weapon - an intellectual credential to convince the public that an idea or process is ‘objective’ and hence better than other competing ideas or processes.” (Ewing, 2011 p. 667). Furthermore, imprecise measures used for informing high stake decisions that benefits societal and institutional interest above individual ones are not unheard of (Glazerman et al., 2010 p. 7). Related to COVID-19 the use of people’s mobility data should be examined and put under scrutiny, which is what I will do in this thesis to arrive at the implications that passive smartphone data had.

## Research question

The motivation to pursue this line of inquiry was driven by an interest in understanding the latest research and advancements in utilizing user data from smartphones in response to the pandemic and was guided by some initial questions. I wanted to know what sources of data was being accessed and utilized for producing actionable knowledge and inform decisions on NPIs. In that regard it was also a matter of getting an overview on the applications the research had on a real-world scenario and the challenges and limitations in acquiring and using this type of data. To narrow in on the above the research question will be:

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What are the implications of collecting passive mobility data from smartphone users and utilizing it for evaluating the effects of non-pharmaceutical interventions during the COVID-19 pandemic?

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The main question will be accompanied by a set of secondary questions:

- Does NPIs work as a preventive measure and if so to what degree?
- How are the passive data generated and which sources are collecting and making them available?
- What metrics and scales are used, and which phenomena and effects can be observed with mobility data?
- How are data privacy and ethical concerns managed?

The purpose of these questions is to answer how data is generated, who provides access to it, what knowledge and insights it provides, and achieving an understanding of what mobility data can tell us about NPIs that restrict movement and travel behaviors. In practice answering the research questions will manifest as a descriptive synthesis of the written content in the publications included in the systematic literature search, which serve as a basis for a following discussion and conclusion. In the next chapter I will go into greater detail about the choices and approaches taken in the research methodology to answer the above questions.

# Research Methodology

The following chapter is concerned with the methodic approach of the thesis. This includes reflections on literature review as a method, explication of choices taken to arrive at a selection of publications that can enlightening the research question and the use of software to support the process.

## Defining the Search String and Inclusion Criteria

The following three databases were chosen for extraction of literature for the review: Association for Computing Machinery (ACM), Scopus and Web of Science. ACM was included due to the databases' general focus on computing and the potential to gain a focused technical perspective. Scopus was included because of its extensive library of multidisciplinary content that could potentially enlighten the research question from multidisciplinary perspectives. Web of Science was included due to its sizeable and diverse corpus, which provides an eclectic mixture of disciplines and fields.

To summarize, the publications had to cover the use of passively generated location data from smartphones in the context of examining mobility and travelling restricting NPIs that regulated mobility behaviors on national levels during the COVID-19 pandemic. To reflect that specific interest I defined a carefully explicated set of inclusion criteria that could be used to delimit the initial literature sample (Wolfswinkel et al., 2013, p. 48).

The inclusion criteria were as follows:

1. The publication study must be in context of COVID-19.
2. The publication must cover or engage with passive smartphone data.
3. The data must originate from smartphone applications, OTT service providers or internet-based sampling in general.
4. The publication must, to some degree, discuss the data mentioned above in relation to mobility regulating NPIs.

The four criteria were interconnected in such a way that only publications that engaged with the intended data of interest in context of mobility regulating NPIs during COVID-19 were included. With the focus on pervasive devices that are seamlessly integrated in everyday life of the user, some technologies had to be excluded. Unfortunately, I had to exclude data from wearables (e.g. smartwatches) due to their lesser popularity and their sensing capabilities being slightly different to those of the regular smartphone.

To find literature, which covered the subject described above, I devised a search string that reflected the topics of interest. Due to the explosion in COVID-19 themed publications, mentioned above, limiting the search year and database numbers was not enough on its own. A rigorous search string also had to be applied and I went through several iterations of search strings to refine and narrow down the results to a manageable number. It was very much a heuristic process of trial-and-error lead by an initial so-called 'brief search' (Rowley & Slack, 2004, p. 35). This initial brief search or read-in to the area of interest helped identify the necessary vocabulary and keywords to produce the search string. The search string was as follows:

(ALL (smartphone? OR phone? OR mobile?) AND ALL ("covid-19" OR coronavirus) AND ALL (mobility) AND ALL (intervention?)).

The first module, which focuses on the technology, is comprised of "smartphone?", "phone?" and "mobile?" all with the added question mark to account for use of plurals in the literature. The three words were chosen based on the brief search and identification of the casual use of all of these to describe the same thing. While "smartphone" is arguably the more precise term it is not as prevalent in use as the other two. The second module, which focuses on context, contains two words "covid-19" and "coronavirus" and were used to narrow in the results to publications that is related to the pandemic. Since "coronavirus" could potentially have been studied prior to the 2019 pandemic the publication data was limited to 2019. The third module "mobility" was included in the search string to catch publications that were occupied with the mobility aspect of NPIs during COVID-19. For the fourth module I found that using the keyword "intervention?" was most accurate for including publications using the NPI (non-pharmaceutical intervention) terminology and those simply referring to it as interventions.

I did not specify the data of interest in the search string since the initial brief search revealed that these are often described with varying vocabulary, varying degrees of thoroughness and at times not explicitly specified at all. The vocabulary used about the sought datasets were "passive", "opportunistic" and "implicit" which provided unnecessary noise when applied to the search string for one apparent reason; It delimited the search from providing publications of interest since the words are not specific to the field of study but used as adjectives for describing a myriad of different things. To my knowledge, no clear consensus on the terminology used for passive mobile phone location data exists.

The search string narrowed in the search to include papers that covers the chosen technology (mobile phone), the context (COVID-19), the area (human mobility), which is inherently occupied with the data of interest, and incorporating the interventions aspect (NPIs). The initial literature search produced a total of 210 hits divided on the three databases with 123 results in ACM, 66 results in Scopus and 21 results in Web of Science. The list of the 210 initial publications, which the search string provided, is available in appendix 1 'Full Literature Draft'. The drafted papers were then evaluated in accordance with the three-phase inclusion/exclusion process.

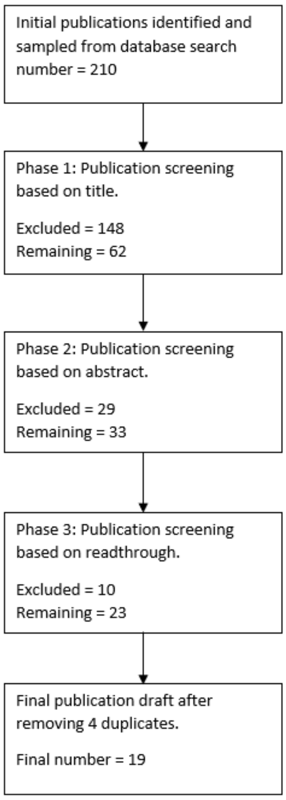

*Figure 1 - Literature selection phases*

I deployed a strategy in three phases to find the relevant articles, which is visualized in figure 1. The strategy's three phases were based on the normative textual hierarchy in publications which reflected: title to abstract to full readthrough.

- Phase 1: Publications with titles that hinted at relevance to the research question were included in the first phase and those that reflected a clear departure from the interest of the thesis were discarded. 62 of the 210 publications were remaining after phase 1.
- Phase 2: The abstracts of publications that were included in the first phase were read to further determine their relevance to the research question. If the abstract explicitly demonstrated content on mobility interventions during COVID-19 they were included. I also included publications that were vague in describing the specifics of e.g. their datasets. If the publication could not be excluded based on the abstract it went on to the next phase. 33 publications were remaining after phase 2.
- Phase 3: The remaining publications were subjugated to a read through until their datasets were confirmed to contain the passive location data from smartphones, and I could confirm their compliance with the inclusion criteria. 23 publications were remaining after phase 3 but removing duplicates narrowed the final selection of literature down to 19 publications.

Performing the literature condensation this way made sure the included publications went under rigorous inspection since they had to pass all three phases to be included in the final selection.
I utilized the software Zotero to assist in the literature condensation process. The structure can be seen in figure 2. I started by importing all material from each respective database into a folder representing the publications origin. Afterwards, I organized three subfolders each representing a phase in the selection process in a descending order. Publications that could be excluded based on their title were not included in the 'phase 1' folder. Publications that could be excluded based on their abstract were included in the 'phase 2' folder. The remaining publications were subjugated to a thorough inspection to make sure they lived up to the inclusion criteria and that their datasets where in fact based on passively collected mobile location data. This occasionally required investigation that extended beyond the content of the publication if the dataset source and content were casually referred to. If validated for inclusion, the final publications were moved to the 'phase 3' folder.

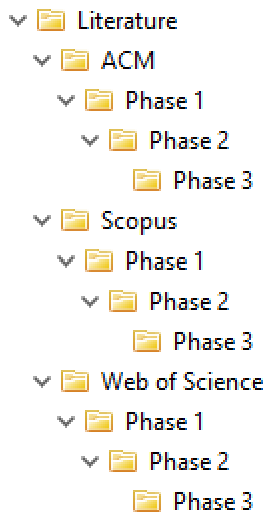


*Figure 2 - Zotero folder management*

Figure 3 below shows the uneven distribution of literature which the search string provided from the three databases. Counterintuitively, the more initial literature a database provided the less was included from it for the final review. There are two likely reasons for this occurrence that I could heuristically identify. Firstly, the difference in the search engine algorithms is likely reflected in the varying results. This could be due to the difference in database size, which makes it necessary for Scopus and Web of Science to be more accurate than ACM that has less content due to its narrower focus. Secondly, the search string and the chosen terminologies could potentially favor the content that is published on Scopus and Web of Science, which is why they had a better inclusion rate than ACM. When duplicates were removed, 19 out of 210 publications were included and the final selection consisted of 4 out of 123 ACM publications, 10 out of 66 Scopus publications and 6 out of 21 Web of Science publications. A complete list of the literature in each phase is available in appendix 2 'Literature Inclusion Phases'.

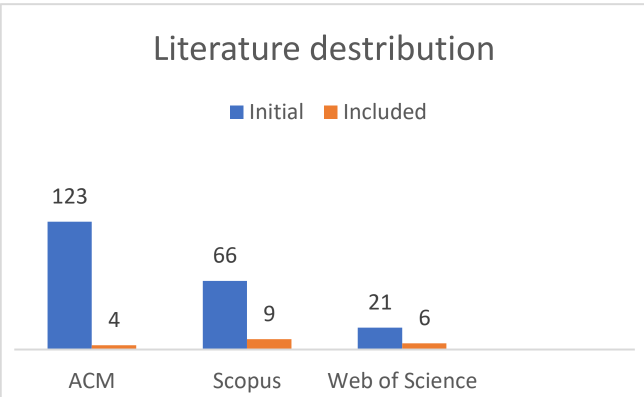


*Figure 3 - Database initial draft vs. final selection*

## Literature Review and Grounded Theory Method

According to Randolph (2009) the key components of the literature review, which parallels primary research, are "(a) a rationale for conducting the review; (b) research questions or hypotheses that guide the research; (c) an explicit plan for collecting data, including how units will be chosen; (d) an explicit plan for analyzing data; and (e) a plan for presenting data.” (Randolph, 2009, p. 4). The rationale and research question are presented above, and the following will account for the plan of the remaining review components.

With an estimated 4% of global research in 2020 being on COVID-19 (Else, 2020), taming the virtual flood of research papers has been attempted by deploying artificial intelligence (AI) to review the literature but the method is far from perfected (Brainard, 2020). Therefore, there is still need for manual literature reviews to make sense of the rapid increase in publications on the topic of COVID-19. With the impressive number of publications on COVID-19 during the pandemic an exhaustive systematic review of all relevant sources was likely not possible with the available time and resources. Therefore, I chose to approach the review from a narrative/semi-systematic approach that deployed a structured search strategy for extracting a carefully chosen selection of studies. The purpose of this methodic constellation was performing a rigorous literature review that could facilitate theory building and produce new insights by analyzing the “(…) emergence of new themes, issues and opportunities; interrelationships and dependencies in or beyond a particular area; as well as inconsistencies.” (Wolfswinkel et al., 2013, p. 45).

| *Number* | *Task* |
|---|---|
| 1. DEFINE | |
| 1.1 | Define the criteria for inclusion/exclusion |
| 1.2 | Identify the fields of research |
| 1.3 | Determine the appropriate sources |
| 1.4 | Decide on the specific search terms |
| 2. SEARCH | |
| 2.1 | Search |
| 3. SELECT | |
| 3.1 | Refine the sample |
| 4. ANALYZE | |
| 4.1 | Open coding |
| 4.2 | Axial coding |
| 4.3 | Selective coding |
| 5. PRESENT | |
| 5.1 | Represent and structure the content |
| 5.2 | Structure the article |

Figure 4 - Five-stage grounded-theory method for reviewing the literature in an area. (Wolfswinkel et al., 2013)

The literature review itself is a form of qualitative analysis with the purpose of: “reading and reflecting; interacting with the literature/data and commenting on it; identifying key themes and coding for them; extracting from the codes 'gold dust' quotes to be used when writing up; linking similar ideas from different articles/ transcripts; identifying contradictions in arguments; comparing dissimilarities in articles/transcripts; building one's own argument/analysis with links to supporting evidence in the data/literature.” (Gregorio, 2000, p. 2). I decided not to perform a meta-analysis due to the lack of randomized control trials (Snyder, 2019, p. 335) and the diffusion of foci and datasets in the research publications selected for the review. Instead, I adopted a qualitative systematic approach where “a strict systematic review process is used to collect articles, and then a qualitative approach is used to assess them.” (Snyder, 2019, p, 35). I deployed a grounded theory research design to approach the task and utilized a five-stage method by Wolfswinkel et al. (2013) for using grounded theory to review literature which is visualized in Figure 4 above. The grounded theory approach to a literature review “are aimed at representing the best available knowledge of a niche or area in which the literature review is performed” (Wolfswinkel et al., 2013, p. 50). The method is considered a viable option for conducting rigorous qualitative research (Charmaz & Belgrave, 2015) and a fundamental premise of the method is to let key issues emerge from the process (Charmaz & Belgrave, 2015, p. 47). The method is sometimes synonymous with an inductive approach (Bryman, 2015, p. 568), about which Charmaz & Belgrave (2015) writes: “That means you start with individual cases, incidents or experiences and develop progressively more abstract conceptual categories to synthesize, to explain and to understand your data and to identify patterned relationships within it”

(Charmaz & Belgrave, 2015, p. 28). Grounded theory, however, is more than just an inductive approach it is also a set of specific procedures (Bryman, 2015, p. 568). The analysis was conducted as a constant comparison analysis which is one of the most commonly used approaches to qualitative data analysis (Leech & Onwuegbuzie, 2011, p. 75). Onwuegbuzie et al. (2015) summarize constant comparison analysis as: "Systematically reducing source(s) to codes inductively, then developing themes from the codes. These themes may become headings and subheadings in the literature review section." (Onwuegbuzie et al., 2015, p. 12). It is an approach where the researcher constantly compare excerpts that have been categorized together while also being sensitive to inter-category contrasts to make theoretical elaboration emerge (Bryman, 2015, p. 568). As prescribed by Wolfswinkel et al. (2013) I performed the constant comparison analysis in three steps moving from open coding to axial coding and finishing with selective coding which they summarize as: "In sum, open coding is the analytical process of generating higher-abstraction level type categories from sets of concepts/variables. Axial coding is the further developing of categories and relating them to their possible sub-categories. With selective coding the categories are integrated and refined." (Wolfswinkel et al., 2013, p. 51).

For performing said analysis I utilized the software NVIVO as a tool to assist in process, as proposed by Gregorio (2000), and the guidelines for using NVIVO for computer-assisted qualitative analysis proposed by Bryman (2015). The reason for deploying NVIVO was to assist me with e.g. recording, storing, indexing, sorting and coding of the literature (Leech & Onwuegbuzie, 2011, p. 71). NVIVO makes it much easier to code sequences of text and arrange those codes in a library while writing memos that work as drafts for the final analysis. It makes organizing and moving the concepts, sub-categories and categories easy and in general assist with the analysis in its entirety.

The analysis started with importing the literature selection into NVIVO and reading through them from one end to another in order to "highlight any findings and insights in the text that seem relevant to the review's scope and research question(s)." (Wolfswinkel et al., 2013, p. 50). The highlighted fragments of text each represented a relevant excerpt that acted as basis for the three-step coding phases (Wolfswinkel et al., 2013, p. 50).

## Three-phase Coding

*"In short, coding is the process of defining what the data are all about."*
*(Charmaz & Belgrave, 2015, p. 37).*

Here I will account for the three coding and how it was utilized in the literature review process.

### *Open Coding*

Open coding is a process where you examine, compare and break down the content of texts into concepts and categories (Bryman, 2015, p. 569). Concepts are first produced through the open coding and are basically labels given to identified phenomena (Bryman, 2015, p. 570). Categories are one abstraction level higher than concepts and are established based on previously identified concept phenomena which can be elaborated and regarded as a 'real-world phenomena' (Bryman, 2015, p. 570). In addition to this, "The ultimate goal of open coding is to identify a set of categories or a bird's eye image of the study's findings, with a set of theoretical and methodological insights attached." (Wolfswinkel et al., 2013). In the first open coding step I re-read the excerpts and arranged them in codes that captured the essence of the data and underlying study on which the text fragment was based while writing memos on findings/comparisons that I perceived as interesting or important to the research question, and then the excerpts were incorporated into a set of concepts, categories and insights (Wolfswinkel et al., 2013, p. 50). Here NVIVO was especially helpful for storing and managing excerpts and notes (annotations) on the texts. This was the first abstraction phase of the literature review and its selected publications and it was performed to "identify, (re-)label and/or build a set of concepts and insights based on the excerpts supported by the papers." (Wolfswinkel et al., 2013, p. 50).

### *Axial Coding*

Axial coding extends on the prior open coding phase by identifying connections between the categories and sorting them into categories and sub-categories by linking them "to contexts, to consequences, to patterns of interaction, and to causes." (Bryman, 2015, p. 569). Figure 5 below served as a guide for linking these relationships between the categories. I used the elements in Borgatti's (1999) framework in the axial coding phase to look for relations between the categories and their concepts which were identified previously in the open coding phase. (Wolfswinkel et al., 2013, p. 50-51). I did this to identify the attributes or aspects of a category (properties) (Bryman, 2015, p. 570) and the interrelations of the categories and develop so-called core categories that represented main themes and patterns in the literature selection (Wolfswinkel et al., 2013, p. 50-51). These categories are outlined in the comparison chapter. In this phase using NVIVO was an advantage and allowed a much easier overview of the already identified content in the literature.

| **Element** | **Description** |
|---|---|
| Phenomenon | This is what in schema theory might be called the name of the schema or frame. It is the concept that holds the bits together. In grounded theory it is sometimes the outcome of interest, or it can be the subject. |
| Casual conditions | These are the vents or variables that lead to the occurrence or development of the phenomenon. It is a set of causes and their properties. |
| Context | Hard to distinguish from the casual conditions. It is the specific locations (values) of background variables. A set of conditions influence the action/strategy. Researchers often make a quaint distinction between active variables (causes) and background variables (context). It has more to do with what the researcher finds interesting (cause) and less interesting (context) than with distinctions out in nature. |
| Intervening conditions | Similar to context. If we like, we can identify context with moderating variables and intervening conditions with mediating variables. But it is not clear that grounded theorists cleanly distinguish between these two. |
| Action strategies | The purposeful, goal-oriented activities that agents perform in response to the phenomenon and intervening conditions. |
| Consequences | These are the consequences of the action strategies, intended and unintended. |

*Figure 5 - Axial coding elements (Borgatti, 1999)*

### *Selective Coding*

The selective coding process integrates and refines the identified core categories and select the main ones based on their relevance to the subject of the review or the research questions and determine their relationship (Wolfswinkel et al., 2013, p. 51). This is to create a single point of reasoning around which the other categories are relationally revolving (Wolfswinkel et al., 2013, p. 51). This is manifested in the 'Discussion' chapter of this literature review.

## Constant Comparison Analysis

The chapter will include a thorough explanation of the content in the publications selected for the literature review. It will start with addressing formal details about the 20 publications and evolve into a narrative and descriptive presentation of their content based on the analysis performed in NVIVO. The purpose is establishing a basis for discussing the results and answering the research questions.

### Corresponding Author's Country of Affiliation

The final selection of studies and their corresponding authors are affiliated with six different countries: USA, UK, Turkey, Canada, Italy and Germany. USA are by far most represented with twelve studies, UK second with three studies and the remaining countries Turkey, Canada, Italy and Germany with one study each.

### Data Sources

Below in Figure 6 is a summary of each publication's country of origin, the mobility data sources they use in their studies and the database it was extracted from, presented in alphabetical order by author. It is an overview that can serve as a help for the reader in distinguishing the literature.

| Author | Origin | Data source(s) | Database |
|---|---|---|---|
| Budd et al | UK | None:review | Scopus/Web of Science |
| Costen et al | USA | SafeGraph | ACM |
| Drake et al. | UK | Google Mobility | Scopus |
| Durmus et al. | Turkey | Google Mobility | Scopus |
| Gao et al. | USA | Descartes Labs, SafeGraph | ACM |
| Hsiehchen et al. | USA | Institute for Health Metrics and Evaluation (IHME) | Web of Science |
| Hu et al. | USA | The University of Maryland (COVID-19 Impact Analysis Platform) | Web of Science |
| Kang et al. | USA | SafeGraph | Scopus/Web of Science |
| Kishore et al. | USA | None: framework suggestion | Scopus/Web of Science |
| Kogan et al | USA | Cuebiq, Apple Mobility | Web of Science |
| Lee et al. | USA | The University of Maryland (COVID-19 Impact Analysis Platform) | Web of Science |
| Mckenzie & Adams | Canada | Google Mobility | Scopus |
| Oliver et al. | USA | None: editorial | Scopus |
| Pepe et al. | Italy | Cuebiq | Web of Science |
| Perra | UK | None:review | Scopus |
| Pesavento | USA | SafegGraph | ACM |
| Roy & Kar | USA | SafeGraph | Scopus |
| Showalter et al. | USA | Skyhook | ACM |
| Wirth et al. | Germany | None:review | Web of Science |

*Figure 6 - Literature basic information*

There are seven different sources of data that is used across the studies in this literature review. These datasets were either freely available, accessible by request or acquired through partnering with a tech company:

- SafeGraph (upon request)
- Google Community Mobility Report (freely available)
- Descartes Labs (upon request)
- University of Maryland COVID-19 Impact Analysis Platform (upon request)
- Cuebiq Mobility Insights (freely available)
- Apple Mobility Trends Reports (freely available)

- Skyhook (partnership)

SafeGraph was particular favored as data source within the literature, which is similar to the review by Perra (2021) who also had a literature sample high on publication from the USA and saw a trend in studies that they categorized under ‘Measuring NPIs via proxy data’ and sub categorized under ‘Adoption of NPIs’ predominantly using SafeGraph as a data source (Perra, 2021, p. 6). Coston et al. (2021) also pointed out the high adoption of SafeGraph’s datasets for scientific purposes during COVID-19 (Coston et al., 2021, p. 175). SafeGraph measures daily visits to over 7 million individual points of interest (POI) from anonymized smartphone devices in North America (SafeGraph, 2021). POIs are made up of locations such as stores, restaurants, schools, museums etc. categorized by e.g. industry and brand. Aggregated SafeGraph data anonymize the individual by grouping people into a geographical resolution called a census block group (CBG) which contains around 250-550 housing units and is a subdivision the statistical geographic unit census tract which typically houses between 4000-8000 people (Environmental Systems Research Institute, 2020).

The Google Community Mobility Reports were used in four of the studies and is a chart of the percentage change in mobility to different places (retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential) on national, regional and municipal geographical units (Google, 2021).

The Descartes Labs data was used in two studies and it contains information on the distance a member of a given population moves in a day on the geographical state and county level in the USA (Warren & Skillman, 2020).

Two studies drew their data from the University of Maryland’s COVID-19 Impact Analysis Platform which offers 39 metrics in four categories (mobility and social distancing, COVID and health, economic impact, vulnerable population) on national, state and country levels in the USA (Maryland Transportation Institute, 2020).

One study used the data made available by IHME which is a collection of other datasets. For obtaining international mobility data IHME use datasets from Google, Facebook and Apple and for mobility in the USA they use Descartes Labs and SafeGraph (Institute for Health Metrics and Evaluation, 2020).

The Cuebiq Mobility Index was used in two studies and quantifies the daily distance a device travels and aggregates the results on a national, state and county wide geographical level (Cuebiq, 2021).

Apple Mobility Trends report was used by one study and is a collection of direction requests in the Apple Maps application per country, region, subregion and city which was compared to a baseline volume of direction requests set prior to the COVID-19 pandemic (Apple, 2020).

Studies approaching research on the relationships between NPIs and mobility behavior during COVID-19 with passive smartphone data seemingly have to rely on aggregated datasets from technology companies who group or cluster individual users into geographical units to anonymize their data.

## Summaries

The following will provide a summary of the content and results of each included publication, presented in a narrative manner so the reader gets a quick introduction to the body of literature and has a basis for understanding the subsequent discussion and categories which the literature will be divided into.

Attempting to create an accurate abstraction of the mobility behaviors and patterns of entire populations is no small task. Getting the right data, applying the correct metrics, data privacy and ethical concerns, bias, socio-economic and demographic variables and contextualizing the data are just some of the responsibilities that cannot be taken lightly. The scale of the COVID-19 pandemic is unlike any event in our lifetime, and it is likely the most intense studied topic to emerge in newer time. Many concerns, variables and perspectives must be incorporated to perform such abstraction in a responsible manner when it is regarding life and death as is the case with the COVID-19 pandemic. The reviewed literature took many different approaches to this task which were all unique in some way.

### SafeGraph & Descartes

One approach found that areas within the city of Los Angeles (LA) that had the highest COVID-19 case counts also had the highest concentration of socially vulnerable people while maintaining the highest mobility rates (Roy & Kar, 2020). They did this by classifying each CBG in Los Angeles based on their cumulative COVID-19 case count and assigning them a low, medium or high vulnerability category which was then compared to sociodemographic indicators and data on mobility from SafeGraph which supported the CBG level comparison on all three parameters because they had the same geographical resolution (Roy & Kar, 2020). This highlighted that the areas associated with the most vulnerable population of LA, and those most likely to die from COVID-19, reduced their mobility the least while most likely to get sick while also being least able to receive medical help and least equipped to pay for medical expenses.

Another American study combined mobility data from SafeGraph with mobility data from Descartes Labs to develop a mobility tracking dashboard (Gao et al., 2020). Using their self-developed dashboard, they found that mobility changes on a national level were somewhat heterogenous but that people living in the states with the highest number of infected in general tended to stay more at home than the states with the lowest number of infected (Gao et al., 2020). This indicated that people likely regulated their behavior based on their home state's COVID-19 infection number. They performed the first part of this analysis by measuring the daily percentage change to median travel distance in a region by combining the max-distance travelled for all unique mobile devices in a region which was then compared to a baseline of mobility prior to COVID-19 being declared a pandemic with data from Descartes Labs (Gao et al., 2020). Additionally, the median of stay-at-home dwell time was scaled up to the state level with data from SafeGraph (Gao et al., 2020).

The high geographical resolution of SafeGraphs datasets were likely the reason for its popularity amongst American studies. The high granularity of the CBG units that SafeGraph aggregated their data in were also used to create a new dataset measuring the human movement between different geographical regions (census tract, county, state) (Kang et al., 2020). They did this by utilizing the home location designated to all unique mobile devices by SafeGraph based on the common nighttime location of the device. By knowing where a device 'belonged', they were able to tell if it left its home CBG and where it went, thus also understanding where visiting devices in a CBG originated from. By performing these measures, the daily change in movement of devices between different areas and regions were revealed. For understanding the dynamic changes of movement within a CBG they measured the weekly visits to POI from devices that that originated in the same CBG as the POI (Kang et al., 2020). This provided an overall indication of the inter-region mobility flow and which geographical units reduced/increased internal mobility and were compliant with NPIs.

Understanding the effect of different NPIs on the COVID-19 transmission was simulated by an American research team who also utilized data from SafeGraph to facilitate the simulation (Pesavento et al., 2020). Interestingly, the simulation indicated that local mobility within a CBG (CBG to POI visits) counterintuitively did not have a significant effect on mitigating the spread of COVID-19 (Pesavento et al., 2020). Based on their simulated results they suggested that the frequency of users staying within a two-meter distance of each other for a at least 15 minutes was a better indicator of social distancing NPIs being complied with than deriving it from average distance travelled per day as is done per the SafeGraph dataset (Pesavento et al., 2020).

Another study that focused on the representativeness of sampling data from smartphone users criticized the validity of data from SafeGraph (Coston et al., 2021). They found that the SafeGraph dataset had a notably skewed coverage of both race and age demographics, which the study deemed problematic since SafeGraph under-sampled vulnerable and at-risk older and minority groups with higher COVID-19 mortality rates (Coston et al., 2021). They proceeded to link this result to potential risk of harming these vulnerable groups if policy did not account for the skewed data representation (Coston et al., 2021). The assessment of the dataset validity was done by comparing the election voter data (age, race, precinct, turnout) with the visits to voting POIs on election day from SafeGraph (Coston et al., 2021).

### Google Community Mobility Reports & Descartes

The other popular data source was the Google Community Mobility Reports, which in the UK was used to evaluate the compliance with NPIs by comparing mobility in the categorized areas (retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential) and observing the percentage change before and after lock-down (Drake et al., 2020).

In a study from Turkey, they used Google's mobility data to measure government top-down enforced NPIs that restricted mobility by comparing mobility changes and growth rate to determine the effect of NPIs and estimate the prevented number of infected people (Durmus et al., 2020). The study indicated that even though the Google mobility data did not directly measure social distancing, the decrease in mobility that could be observed from the data correlated with a decrease in the growth rate and therefore depicted that social distancing was practiced by the population (Durmus et al., 2020).

The data from Google was also used to compare mobility changes around the world with the stringency index, developed at the University of Oxford, which tracks and measures NPIs implemented by governments in 149 countries around the world (McKenzie & Adams, 2020). They found a considerable difference in the delay (lag time) between government implemented NPIs and people decreasing their mobility behavior when comparing countries (McKenzie & Adams, 2020). The lag time averaged at 2.4 days but varied between almost no delay at all to over a week which was linked to a country's level of development (gross domestic product, life expectance, infant mortality deaths) (McKenzie & Adams, 2020, p. 12-13).

A combination of mobility data from Google, Facebook, Descartes Labs and SafeGraph were used in an American study to investigate how political affiliation (Democrat, Republican) in the USA affects compliance with NPIs by measuring reduction in mobility change and comparing it to political party affiliation on a state level (Hsiehchen et al., 2020). They concluded that political orientation affected risk perception which manifested as republican states and areas being less likely to comply with top-down mobility restricting NPIs and democratic states and areas more likely to comply with such interventions (Hsiehchen et al., 2020, p. 111).

### COVID-19 Impact Analysis Platform

Utilizing the 'COVID-19 Impact Analysis Platform', developed by University of Maryland, a study determined the individual effect of multiple different factors on human mobility (Hu et al., 2021). They found that top-down NPIs only contributed with a 3.5%-7.9% decrease in mobility and that variables such as the virus case number, the weather, socio-demographics (population density, employment density, gender, age, ethnicity, median income, etc.) and industries in an area also affected mobility (Hu et al., 2021).

Understanding the mobility response to COVID-19 itself and NPIs was also investigated in another study that extracted data from the 'COVID-19 Impact Analysis Platform', which found that geographical groups with higher population density and income tended to decrease their travel distance the most, while low population density and income groups could be observed reducing their travel distances less after NPIs were implemented (Lee et al., 2020). They proceeded to suggest a method for estimating if the increase in people staying at home was due to citizens working from home (teleworking) or unemployment by comparing the reduction of the mobility metric work trip frequency per person and the weekly unemployment claims from the United States Department of Labor (Lee et al., 2020, p. 8).

### Cuebiq & Apple Mobility Trends Report

In Italy Cuebiq data was used to showcase how aggregated data could potentially be used to evaluate the reduction in mobility caused by the NPIs by measuring the movement between provinces, the travel range of users and the number of unique contacts a person had on a typical day (Pepe et al., 2020). One study used mobility data from Cuebiq and Apple and found that the data was not able to observe a change in virus case numbers and deaths until 2-4 weeks after NPIs were implemented (Kogan et al., 2021).

### Skyhook

Data from the location service provider Skyhook was used to investigate how NPIs in the USA affected tribal communities in New Mexico, which uniquely found that mobility in these areas went up after NPI went into effect (Showalter et al., 2021).

## Reviews

Three studies were literature reviews and did not directly work with datasets. One of these reviews placed mobility data in a larger context of digital technologies used during COVID-19 and found that mobility data were primarily used to evaluate NPIs by providing insight into mobility patterns and argued that mobility data is serving the purpose of interrupting community transmission in tandem with digital contact tracing applications (Budd et al., 2020).

A second review on digital technologies identified the different use cases for technologies being utilized during COVID-19 and found that the literature on these technologies had a tendency to be highly specialized and only considered a single use-case, meaning exclusively focusing on contact tracing, mobility tracking, outbreak detection or location based risk assessment (Wirth et al., 2020). They concluded that the singular focus resulted in an untapped potential in multiple use case solution that was stunted by the lack of guarantied data privacy (Wirth et al., 2020).

The final review narrowed in on a large corpus of literature on NPIs during COVID-19 and categorized the literature into seven different categories: epidemic models, surveys, comments/perspectives, papers aiming to quantify the effects of NPIs, reviews, articles using data proxies to measure NPIs, and publicly available datasets describing NPIs (Perra, 2021, p. 1).

## Comparison

This chapter will be the start of synthesizing the literature by comparing the content of the publications. The written content is a result of the axial coding phase.

As demonstrated above in the summary, the passively collected data that people's smartphones generate and collect about their movement and travel patterns every day is used for many different purposes in the literature. While the field of studies that pursue these interests also deploy other data (e.g., CDR) and technologies (e.g., smartwatches), my selection of literature displays a more particular selection based on the specific type of passive mobility data from internet-enabled smartphones which were part of the inclusion criteria for said literature.

## Metrics

To clarify what exactly 'mobility data' means, this part will examine the different approaches to quantifying this concept and its building blocks. It is going to be an examination of how the studies answer the questions "how can movement be reflected in data? How can movement be characterized?" (Andrienko et al., 2008). This is to elucidate how the studies utilize mobility data to understand NPIs and COVID-19. Kishore et al. (2020) suggest a framework with the most essential aggregated mobility data metrics and a common vocabulary, so that metrics are easier to compare across studies. I will compare the metrics in the selected literature based on the mentioned framework.

**Distance travelled** is a measure used to determine the amount of movement taking place within a population and set timeframe and does so by registering the distance between start and stop points of a device (Kishore et al., 2020, p. e625). It Is also referred to as 'individual max-distance' (Gao et al., 2020), 'median travel distance' (Gao et al., 2020) and more commonly 'travel distance' (Hu et al., 2021; Kang et al., 2020). Measured decrease in population travel distance has been linked to a decrease in infection rate when accounting for the delay due to COVID-19's incubation period (Kogan et al., 2021, p. 6). As previously established, the incubation period is typically 5-7 days. Due to a combination of the correlation between decreased travel distance and COVID-19 infection numbers, and COVID-19 mainly transmitting through person-to-person contact, the distance travelled metric is assumed to indicate social distancing and NPI compliance as a proxy (Kogan et al., 2021). This is the case with e.g. the SafeGraph dataset where on average distance travelled per day is used as an indicator of social distancing (Pesavento et al., 2020, p. 34). Despite the assumptions by some studies that the distance travelled to some degree indicate social distancing it is deemed insufficient as a standalone metric by others (Hu et al., 2021, p. 2). One study explicitly stated that reduced mobility and social distancing were not mutually ensured (Gao et al., 2020, p. 25). Instead, other metrics are suggested for a better indication of the compliance with NPIs and in particular compliance with social distancing orders.

The **Population distribution and dynamics** metric is used to determine the amount of devices spending their time in specific areas or places such as parks, residential areas or for example certain types of stores (Kishore et al., 2020). Sometimes casually referred to as 'number of visits' in relation to POIs (Coston et al., 2021; Roy & Kar, 2020), or 'place based activity patterns' (McKenzie & Adams, 2020). The metric has been used for gaining an overview of national changes to mobility in different areas (described above) and correlating the mobility change with a prevented number of infected individuals (Durmus et al., 2020). It has also produced insight on the weekly percentage change to mobility in these different areas and evaluating how NPI compliance gradually decreased over time (Drake et al., 2020). Comparing this mobility metric with socio-demographic variables on geographical units was helpful for understanding how mobility change in response to NPIs varied across low-high income areas (Roy & Kar, 2020). On an international scale, it was used to observe a -100% to +497% change in mobility compared to a set baseline (McKenzie & Adams, 2020). It can also serve as a basis for simulating the effect of different NPI on mobility (Pesavento et al., 2020).

**Measures of staying put** are used to determine how much time a device spends at a single location and are usually seen utilized to determine how much time is spent at the assigned home location of the device (Kishore et al., 2020). It is also referred to as 'home dwell time' (Gao et al., 2020), the 'proportion of staying home' (Hu et al., 2021), 'stay-at-home' (Roy & Kar, 2020) or 'propensity to leave home' (Pesavento et al., 2020). The home location of a device is assigned based on the location it spends most nights over a six-week period (Gao et al., 2020) or where it spends the most time from a set of location frequently visited (Kishore et al., 2020). Measures of staying put was most commonly used in combination with distance travelled to account for the effect of NPIs on mobility (Gao et al., 2020; Roy & Kar, 2020). These data on the home location of devices were used to measure the percentage change on multiple geographical scales (Gao et al., 2020) and some added sociodemographic variables to see how staying put varied across e.g. income and population density (Roy & Kar, 2020). Measures of staying put is considered a direct quantification of the response to NPIs that encourage people to stay more at home (Hu et al., 2021). Home location are also assigned at different geographical units as for example the home region of a device (Pepe et al., 2020).

Assigning devices a home location can be used to determine the **transition between regions,** which estimates the mobility between a set of geographical units by measuring the number of devices moving from one region to another (Kishore et al., 2020). The studies using this metric did so under the name of 'origin-destination matrix' (Pepe et al., 2020) and 'dynamic origin-to-destination (O-D) population flow' (Kang et al., 2020). The transition between regions can be performed at different geographical scales and the highest resolution it has been performed at is the CBG level, where it assisted in estimating the effect of NPIs by measuring how many people stayed home and how many moved to other regions compared to a baseline (Kang et al., 2020). One study argues that metrics on the transition between regions while collected daily are best for performing weekly observation due to the societal structure of the 7 day week being highly regular (Kang et al., 2020). It has also been used to observe the change in 'out of county' trips compared to population density, which revealed that low-density areas transition less between regions than populations from high-density regions (Lee et al., 2020).

**Trips per person** was used to observe changes in trips categorized by work and non-work trips (Lee et al., 2020). One study suggests that despite the lack of contextual information in this metric it has been able to show correlation between reduced mobility and drops in COVID-19 infection rates when adjusting for the incubation period of COVID-19 (Kogan et al., 2021). Another study did this by measuring the daily average number of trips per person by dividing the registered trips with the area population to see the mobility change over time (Hu et al., 2021).

The approach of establishing a baseline based on previous data on mobility patterns is commonly seen utilized or mentioned across studies (Coston et al., 2021; Drake et al., 2020; Gao et al., 2020; Kang et al., 2020; Kishore et al., 2020; McKenzie & Adams, 2020; Pepe et al., 2020; Showalter et al., 2021). The time periods that established the baselines across the studies varied between 1-5 weeks, and overall explanation and rationale for setting the baseline period was lacking, making the process seem arbitrary. Seen as the reported changes in mobility are relative to the set baseline one would think this of greater importance for both reliability and validity.

Although difficult to gain access to at first, due to the widely vocabulary used about the metrics, the studies use a relatively small selection of mobility metrics that can be placed within five categories. Below is accounted for the utilized metrics and how they are distributed on the various studies:

- The **distance travelled** metric was used in six of the studies (Gao et al., 2020; Hu et al., 2021; Kogan et al., 2021; Lee et al., 2020; Roy & Kar, 2020; Showalter et al., 2021)**.**
- The **population distribution and dynamics** metric was also used in six of the studies(Coston et al., 2021; Drake et al., 2020; Durmus et al., 2020; McKenzie & Adams, 2020; Pesavento et al., 2020; Roy & Kar, 2020).
- The **measures of staying put** metric was used in six of the studies as well (Gao et al., 2020; Hsiehchen et al., 2020; Hu et al., 2021; Lee et al., 2020; Pesavento et al., 2020; Roy & Kar, 2020)**.**
- The **transition between regions** metric was used by three studies (Kang et al., 2020; Lee et al., 2020; Pepe et al., 2020)**.**
- The **trips per person** metric was seen utilized across three different studies (Hu et al., 2021; Kogan et al., 2021; Lee et al., 2020)**.**

It is evident from the above that the aggregated datasets in general provide data that can be categorized into five metrics. In summary, the **distance travelled**, **population distribution and dynamics** and **measures of staying put** are used equally across the studies. **Transition between regions** and **trips per person** are less utilized in the sampled literature. There is a significant variance in the vocabulary used to describe these metrics which is indicated by the almost complete lack of a common language between studies. Furthermore, different metrics are attributed varying levels of meanings regarding their indication of e.g. social distancing. These findings are consistent with that of Perra (2021) who also found a lack of standardized metrics in studies during COVID-19. The lack of standardization on multiple levels makes it difficult to perform more than casual comparison between the results of the studies.

The aggregated data metrics are characterized by division based referencing into geographical hierarchies (Andrienko et al., 2008). The next chapter will go into greater detail about the geographical divisions made and their uses.

### Aggregation Scale

The data was aggregated and scaled to various geographical units representing groups in a population. These ranged from international units to POI units of specific location. Mobility changes in different sectors on a national level were used to compare the difference in overall mobility change and response to NPIs across countries (McKenzie & Adams, 2020). Similar mobility data, on a national scale, was used to compare the percentage drop in mobility, across different sectors, to the COVID-19 reproduction number and establish a number of infections that NPIs had prevented (Durmus et al., 2020).

Another study evaluated the effect of NPIs by observing the national drop in mobility across different sectors (Drake et al., 2020). Similarly on the regional state level data was used to compare mobility in each state with the corresponding COVID-19 case number to determine that the number of infected had an effect on mobility (Gao et al., 2020). These mobility data were used to find the direct effect of NPIs on the number of infected, how the COVID-19 infected number affects mobility and how NPI affected mobility. It indicates that mobility can be used from multiple perspectives but ultimately is best suited for asking questions of ‘how’.

Data aggregated on the level of Italian provinces were used to determine the flow of people between regions and each individual region’s mobility change as a response to NPIs (Pepe et al., 2020). Same type of inter-region analysis was performed in USA but with data aggregated on the CBG and POI level (Kang et al., 2020). The device movement between CBGs and POIs units were used to determine changes in mobility and compliance with NPIs on the CBG level (Kang et al., 2020). At the same time this showcased that higher resolution measurements make it possible to observe the dynamic mobility flow of devices between areas that can be scaled up to get information on inter-regional population movement. The higher granular scale that mobility data is aggregated at increases the legal, ethical and privacy concerns (Budd et al., 2020).
Measuring on the CBG level further revealed differences between mobility changes to NPIs in low and high density groups and low and high income groups (Lee et al., 2020). There is a tendency for geographical areas associated with low income to respond less to NPI, which can be observed by less reduction in mobility (Lee et al., 2020). This is observed on both international levels (McKenzie

& Adams, 2020) and regional (Roy & Kar, 2020). A heuristic evaluation of this could attribute it to poorer areas potentially having less access to media and news outlets, a greater distrust to government and therefore less willingness to comply or perhaps difference in risk perception across demographics. Simultaneously regional units (states) were reported to show a decrease in mobility relative to their current infection rate (Gao et al., 2020). When scaling down to CBG level the opposite was seen in some instances where units with the highest number of infected had the smallest decrease in mobility (Roy & Kar, 2020). The insight above indicates that while some phenomena can be observed on widely different scales others cannot be measured if the geographical resolution is too low. This implies that multi-scale measurements are imperative for generating actionable knowledge for policy making. Assigning the geographical units additional labels made it possible to differentiate between rural vs non-rural units and tribal vs non-tribal units at the CBG level for a higher granularity analysis of mobility differences between the assigned labels (Showalter et al., 2021).

It is evident that mobility data has use cases on multiple geographical scales. In a hierarchical order the units identified in the review are: national, regional (state, province, county), CBG and POI.

The studies varied in the scale they performed the research on from the international level, comparing countries, to POI representing a specific location:

- Six studies used the **POI** unit as a scale for their research (Coston et al., 2021; Hu et al., 2021; Kang et al., 2020; Lee et al., 2020; Pesavento et al., 2020; Roy & Kar, 2020).
- Eight studies used **CBGs** as an geographical scale for their research (Coston et al., 2021; Gao et al., 2020; Hu et al., 2021; Kang et al., 2020; Lee et al., 2020; Pesavento et al., 2020; Roy & Kar, 2020; Showalter et al., 2021).
- Two studies looked at the **region/state**-level mobility (Hsiehchen et al., 2020; Kogan et al., 2021; Pepe et al., 2020).
- Two studies investigated mobility on a **national** level (Drake et al., 2020; Durmus et al., 2020). Both studies got their data from the Google's Mobility Report.
- One study looked at the **international level** to compare countries (McKenzie & Adams, 2020).

As visualized above, the studies preferred research on the smaller scales with POIs and CBGs being heavily favored. This is likely due to the studies being predominantly from the USA where other reviews have found SafeGraph to be particular utilized for its high granular dataset (Perra, 2021).

### Contextualizing Mobility Data

The use of additional datasets to contextualize the mobility data was common practice and among mentioned variables in the literature are: age, race, gender, political affiliation, weather, income, employment rate, population density, COVID-19 infection numbers, industries in an area, physical environment and NPI stringency. Some of these variables were treated only as casual explanations for observed mobility phenomena.

The variables in e.g. age, gender, race, ethnicity and socioeconomic status can be important when collecting a representative data sample (Coston et al., 2021; Kishore et al., 2020). At the same time, they are important tools for contextualizing the mobility data providing it with meaning and the ability to distinguish between geographical units. In doing so, one study pointed to the physical environment playing a role in how effective changes in mobility are at reducing social distancing at certain location without processing the topic more (Drake et al., 2020). The same study uses the weather as a casual explanation for the changes in mobility observed at parks (Drake et al., 2020). Population density and median income of geographical units were also applied to establish a context where the changes in mobility could be attached (Lee et al., 2020).

One study tested a range of additional variables population density, employment density, gender, age groups, race, income and proportion of college students to find out which showed similar results across regions (Hu et al., 2021). They proceeded to suggest that the COVID-19 infection number, age, racial distribution, political affiliation and weather were affecting compliance with NPIs and mobility reduction the most (Hu et al., 2021). One other study was in particular focused on the different mobility response to NPI compared to political affiliation, which found that republicans tended to respond less than democrats (Hsiehchen et al., 2020).

Another study suggested that socially vulnerability was a significant variable (Roy & Kar, 2020). Only one study was sensitive to the difference in NPI stringency and the effect on mobility changes (McKenzie & Adams, 2020). Counterintuitively, the higher stringency the more response lag time could be observed in mobility changes (McKenzie & Adams, 2020). Assigning rural and non-rural labels to geographical units were also used as a way to distinguish blocks from each other (Showalter et al., 2021).

Not all studies utilized additional datasets or applied explanations to fill the gaps in the knowledge they created by analyzing mobility data. It is evident that additional variables are used to interpret the data heuristically and through comparative analysis.

### NPI Effects and Mobility Phenomena

This part will go into detail about the indication on human behavior which are suggested in the literature and narrow in on the effects that NPI has on mobility behavior and if they work as intended.

As established above, mobility data can provide some indication of a population's movement and how that changes on spatiotemporal variables. Looking at human behavior through the lens of mobility data the studies observed and described certain phenomena. It was observed that prior to NPIs being implemented mobility would drop in most regions but most noticeably in regions where the COVID-19 infection number was rising the most (Hsiehchen et al., 2020; Hu et al., 2021). This is also referred to at bottom-up behavioral change, as opposed to top-down change instigated by NPIs (Perra, 2021, p. 38). In America, the state median of distance travelled was observed to change heterogenous but dropping by as much as 73% compared to a baseline set before NPIs were implemented (Gao et al., 2020). At the same time, it was observed that mobility would surge shortly before COVID-19 was declared a pandemic, which is associated with people reacting to the uncertainty and potential NPIs and is dubbed 'pre-pandemic panic' (Hu et al., 2021). There exists an observed lag in the time between NPI implementation and responding mobility change (Hu et al., 2021). Simultaneously on an international scale a delay in observable changes to mobility varied from almost immediate response to over eight days (McKenzie & Adams, 2020). In the USA the response to NPIs were gradual and plateaued after approximately two weeks (Hu et al., 2021). The amount of lag time from NPI to decrease in mobility on an international scale was associated with country development indices such as life expectance, gross domestic product (GDP) and market size (McKenzie & Adams, 2020).

A similar observation was done on the CBG scale in the USA where the areas of a city with the highest concentration of socially vulnerable population (low median income, high percentage unemployment rate and disabled population) also displayed the highest mobility activity and COVID-19 case numbers (Roy & Kar, 2020). This was supported by another study that found that areas with low density and low median income had a less pronounced response to NPIs (Lee et al., 2020) and in some cases were observed to actually increase mobility after NPIs were implemented (Drake et al., 2020; Showalter et al., 2021). On the other end of the spectrum, areas with high population density and areas with high median income tended to stay more at home (Lee et al., 2020).
There are several casual explanations being offered for the low income and density areas increasing their mobility. The high correlation with areas being socially vulnerable is speculated to be due to the population being blue collar service sector workers (Roy & Kar, 2020). People working in such sectors are likely considered essential workers during COVID-19 and might not be able to minimize their mobility as much since for example teleworking is not an option. Furthermore, it is speculated that people living in these areas have to travel further to work and travel further to get supplies due to the limiting circumstances caused by the NPIs (Drake et al., 2020; Showalter et al., 2021). This to some extend indicates that NPIs potentially can cause harm to those communities that are most at risk and are most affected by COVID-19.

Other than population density and median income, political affiliation was found to affect mobility change and NPI compliance on regional scale (Hsiehchen et al., 2020). The difference in mobility change in response to NPIs on a state level correlated with political affiliation of that state and republican states tended to decrease their mobility less than democratic states (Hsiehchen et al., 2020). The study indicated that for every 10% republican population in a region the mobility change in response to NPIs dropped 8% (Hsiehchen et al., 2020). Looking for a casual explanation it could be associated with different news and media consumption and difference risk perception as an effect of that. Despite difference in the response to NPIs on a state level, the implementation of NPIs made the mobility reduction more equal (Lee et al., 2020). Heterogenous regional response and compliance to NPIs were, however, not found to be a tendency on international scale (McKenzie & Adams, 2020). Unlike in the USA, more often than not, the response to NPIs were consistent across regions in a country (McKenzie & Adams, 2020). This is one of two identified discrepancies between American findings and international perspective. An American study estimated the effect of NPIs on decreased mobility to only account for a 3.5%-7.9% change and that increase in infection numbers was likely to cause a larger mobility decrease (Hu et al., 2021). Based on international observations, another study suggested the opposite and stated that mobility activity was more likely to drop from NPIs implemented by government than the reported COVID-19 case numbers (McKenzie & Adams, 2020). This is the second identified difference between observations made in the USA and International observations.

NPIs has been observed to only last for about a month before slowly rebounding and this quarantine fatigue phenomenon is described as the rebound of mobility happening after a short while and is initially characterized by people starting to take more daily trips over a short distance (Hu et al., 2021). NPIs are a preventive measure and it is suggested that their effectiveness is dependent on the time of their implementation (Perra, 2021). In the USA it was observed that, despite more people staying home and the distance and trips per person decreased, the infection number grew rapidly (Hu et al., 2021). If this is an indication of NPIs not working or NPIs being implemented is difficult to conclude. Furthermore, despite NPIs being in effect mobility could be seen spike on holidays and days that are considered travel days (Hu et al., 2021).

### Limitations of Big Data, Privacy and Ethics

This part will go into details about data privacy of aggregated data and the ethical consideration of the publications.

Concerns about legality, ethics and data privacy increase with the resolution of a dataset (Budd et al., 2020). It is considered a challenge to find a balance between using big data for effective analysis which in the case of COVID-19 is utilized to save lives and protecting the data privacy of the individual. Several studies claim that the aggregating method anonymizes the data so it does not reveal information about an specific person's activities (Coston et al., 2021; Drake et al., 2020; Kang et al., 2020; Kishore et al., 2020; Showalter et al., 2021). While the aggregated datasets do not reveal information on an individual level, it does not mean that it cannot reveal such private information. One previous study on the privacy of mobility data found that it was possible to recover the trajectory individuals with a high degree of accuracy from aggregated dataset which proved a serious privacy leakage in this type of dataset (Tu et al., 2018).
These anonymization techniques are becoming increasingly ineffective as the volume of data and the sophistication of the analytical tools are growing (Mehmood et al., 2016). Furthermore, anonymization techniques, such as aggregation, are best suited for static data and not dynamic datasets (Mehmood et al., 2016) such as those used by the studies in this literature review. It is recommended that future solutions use modern privacy-enhancing techniques (Wirth et al., 2020).

Another previous study points to the need of more efficient privacy techniques being developed to handle the increasingly large quantities of low quality data from various different sources (Jain et al., 2016). Aggregated data is however considered a viable option for obtaining data in accordance with the general data protection regulation (GDPR) (Hu et al., 2021; Pepe et al., 2020). Simultaneously aggregated data is also being considered inherently biased because data companies, such as Cuebiq and SafeGraph, do not disclose the applications from which the data originates (Coston et al., 2021, p. 173). The lack of transparency with aggregated datasets is consistently reported as a limitation due to the missing information on the aggregation methodologies (Budd et al., 2020; Coston et al., 2021; Kishore et al., 2020; McKenzie & Adams, 2020).

Studies express a general concern about the privacy of these aggregated big datasets and some more specifically about the loss of data privacy and civil liberties in the wake of COVID-19 where these big data methods are used when the pandemic is over to continue collecting information on citizens permanently (Budd et al., 2020; Oliver et al., 2020).

This indicates there are two main concerns:

1. Government or other entity maliciously using citizen location data during COVID-19 and continue to do so afterwards.
2. Aggregated datasets from big tech companies not being secure and maintaining data privacy despite claims of ethical use.

When the pandemic is over these two elements should be audited further to find out if individuals and demographic groups were being maliciously targeted and if the datasets were as secure as they have been claimed to be.

Another issue with the aggregated datasets, and big data in general, is that the results are up to a fair amount of interpretation (Boyd & Crawford, 2012). It could be argued that mobility data has allowed us to observe that NPIs are biased in their insensitivity to socio-demographic factors since areas associated with a high percentage of socially vulnerable people and low income are most affected and least able to reduce their mobility (Roy & Kar, 2020). But how should this be interpreted? One could conclude that low-income areas are less willing to comply with stay-at-home orders and therefore should be regulated by implementing increasingly stringent NPIs resulting in e.g. monetary fines and potential jailtime if not adhered to. A different conclusion could be that certain NPIs does not work in practice due to circumstances unaccounted for. This could indicate that NPIs are favoring white collar workers who have opportunities to work from home or can afford to not work at all for a limited time. If you live paycheck-to-paycheck this is problematic. At this point it becomes a philosophical question on the role of government and to what degree personal responsibility is with the individual person. If ethicality is only equated with the boundaries of the law, it is essentially bureaucratic.

## Discussion

This chapter will contain a discussion on the previous analysis based on six critical discussion points on the use of big data by Boyd & Crawford (2012) as a framework for performing this task.

Mobility data can undoubtedly provide insight and knowledge on the dynamic and spatiotemporal nature of human movement. In the hands of the right people these big data can serve as a valuable tool for creating actionable knowledge that supports decision makers in implementing NPIs strategically. However, just because the approach is useful, it does not mean that it has no questionable implications.

### Big Data Changes the Definition of Knowledge

Is it good enough to simply track and measure what people do without understanding why they do it or "Do the numbers speak for themselves?" (Boyd & Crawford, 2012, p. 666). When accessing these aggregated big data sets, we must reflect on what people are being reduced to by abstraction. The individual is removed and is reduced to a part of a geographical unit (State, CBG, POI, etc.). The human becomes a predefined set of measurable variables that can be summated as a single digit (distance travelled, trip per person, home dwell time, etc.). When these studies are performed on their own, they are devoid of a deeper understanding of the human conditions that drives and creates the patterns they observe. When heuristic assumptions are made, which is seen at times in the studies, it is at least a good indicator that the scientist is not oblivious to a context behind the numbers. As pointed out by another review, digital technologies are a useful tool but "(…) they are not a silver bullet" (Budd et al., 2020, 1189). Using big data and more specifically mobility data can assist in understanding the patterns of mobility and monitor changes daily, but it cannot fix the problem for us or provide all necessary information.

### Claims of Objectivity and Accuracy are Misleading

Boyd & Crawford (2012) suggest that to make statistical claims based on data it is necessary to know where the data comes from (Boyd & Crawford, 2012, p. 668). This might prove to be a critical weakness in the literature that utilizes these aggregated datasets from big tech companies. The lack of transparency is a recurring theme in the literature (Budd et al., 2020, 2020; Kishore et al., 2020; McKenzie & Adams, 2020). It is explicitly stated as the most notable limitation of using these big data sets (McKenzie & Adams, 2020) and raises fundamental questions of the representativeness (Coston et al., 2021; Kishore et al., 2020) and inherent bias of the method (Coston et al., 2021). This skewedness of representation and inherent bias was first mentioned in the previous chapter 'Limitations of Mobility Data'. There is a fair amount of interpretation happening before the data gets in the hands of the scientists and then it is interpreted some more. The lack of standardization of both the sampling and analytical methods overshadows objectivity and accuracy claims (Budd et al., 2020; Perra, 2021).

The preferred method for proving reliable, objective and accurate results is comparing those results to a similar dataset from another data provider. If comparing multiple datasets suffering from the same limitations it is questionable what the approach proves.

## Big Data are Not Always Better Data

A fundamental question is if these observations could be made without the use of big data relying on aggregated and untransparent datasets from the private sector, and if we can justify going big? A previous study found that the missing theoretical framework for mining spatiotemporal data on people's mobility is a particular challenge for performing research on the area (Nanni et al., 2008). Again, the fundamental issues with missing transparency and standardized metrics are a problem.

What the big data approach can do, perhaps better than other approaches, is provide the big picture and overview of where to focus other research efforts. It can guide us and point us in direction of where we need to look. An example of this is the insight that population groups least able to reduce their mobility are those most at risk, which results in already at-risk groups being more exposed to COVID-19. Big data cannot provide much reasoning for this phenomenon beyond a casual interpretation. Hopefully, future research can use findings like this to identify relevant venues of research so we achieve the knowledge of why these phenomena occur, observe the context behind the big data and are enabled to act on such a problem. Big data in the form it has taken during COVID-19 can support many good initiatives but, due to the current limitations, it should be used with caution in decision and debate.

It is difficult to imagine an approach that can match big data when it comes to providing near real-time information on the scale that it does. The use of people's personal devices as part of a sensory network is an opportunity that has equal parts potential for good as it has for abuse. Not having big data available as a tool for good would be a shame and hopefully it can be tamed in the future. However, there is an inherent hybris in attempting to access near omnipotent quantities of information with the purpose of changing people's behavior. Beyond the scope of this literature review lies a discussion on the ethics of governments using citizen data as basis for deciding the degree a population should be regulated in its behavior.

## Taken Out of Context, Big Data Loses Its Meaning

Maintaining context in big data sets can be a challenge (Boyd & Crawford, 2012, p. 671). This will often require additional data and background knowledge (Andrienko et al., 2008).

The studies in general apply some secondary or additional data source to contextualize the mobility data and some apply context with interpretive explanations as established in the chapter 'Contextualizing Mobility data'. Some of the studies using finer granular data were able to find interesting differences across demographics and geographical areas. This opens lines of inquiry for other research fields that are perhaps better equipped to answer the questions of why certain phenomena are appearing and how to deal with them in an ethical way that focuses on public health. Big data is a tool that can effectively evaluate and assess the general situation.

An example of how using big data misses some vital context in a situation such as COVID-19 is that it cannot on its own consider or account for the long-term effects of NPI being and place and how lock-down and quarantine affects people's mental and physical health. This requires background knowledge or other fields of research to help shed light on such problems.

## Just Because it is Accessible Does Not Make it Ethical

"(…) it is problematic for researchers to justify their actions as ethical simply because the data are accessible." (Boyd & Crawford, 2012, p. 672). The point made by Boyd & Crawford (2012) is that data can be de-anonymized and is at times used without the knowledge of the user (Boyd & Crawford, 2012, p. 672). The studies in the literature review made use of aggregated big datasets where the grouping of individual's data into geographical units is the method for anonymizing the dataset. This is mentioned in all the studies to different extends. If any further justification is provided at all, the studies justified the use of these datasets by the virtue of the sampling being taken from devices that 'opted-in' by consenting to terms of use (Coston et al., 2021; Hu et al., 2021; Kishore et al., 2020; Kogan et al., 2021; Pepe et al., 2020; Showalter et al., 2021). While terms of use might be a legal indicator it is not necessarily an ethical one. Since people are not aware of what data is being collected about them from their personal devices it is questionable if terms of use can be considered appropriate consent (Drake et al., 2020, e386). Terms of use as an ethical consent form assumes that the user of an application do two things; Firstly, the user reads the terms and secondly, the user understands the terms which is questionable at best.

While data privacy was in the peripheral of all the studies to various degrees, it seldom got more attention than an honorable mention. At this point, data privacy seems more like a mandatory line that must be repeated rather than something that is engaged with. On this issue another study describes it as a naïve view on the topic of digital data privacy among the sciences (Wirth et al., 2020). A previous study points to the missing consensus on what privacy is in relation to big data (Bonchi et al., 2008). One study pointed out the concern that the interest in data is working under the guise of a malicious purpose to collect surveillance data on citizens after the pandemic is over (Budd et al., 2020). Tracking people's compliance with government regulation based on computed movement patterns are a serious concern when it comes to civil liberties and privacy (Budd et al., 2020).

The need for innovative new privacy solutions (Wirth et al., 2020) and systems that are guarded against invasion of privacy (Budd et al., 2020) are likely going to be a product of government regulation that makes companies responsible as have been done with the General Data Protection Regulation (GDPR) in Europe. Such regulations might be a step in the right direction for future data privacy. It becomes a problem if data privacy protection is too expensive for big tech companies to share their data. Despite the issues that have been established so far there are many interesting and insightful results coming from those data and it does provide new and valuable knowledge. It would be a shame if the potential and opportunities of the big data approach eluded us in the future.

## Limited Access to Big Data Creates New Digital Divides

Boyd & Crawford (2012) initiate this part of their discussion by asking "who gets access to big data? With what purpose, context and constraints?" (Boyd & Crawford, 2012, p. 674). In the selected literature for this review, two categories of discussion, which are apparent in relation to the limited access and digital divide of big data, are identified.

Most of the datasets used by the reviewed studies are freely available or can be obtained by request. However, a prominent theme is the lack of transparency associated with these aggregated datasets. In general, it was reported as a limitation of the studies and as such it is identified as a key limitation of the studies in this review. Another implication of this divide is the difference in data availability between continents. Different data providers combined with the lack of transparency regarding the methodology makes it difficult to compare across continents. Another layer is added to this by the missing standardization of metrics (Perra, 2021) and vocabulary (Kishore et al., 2020) which established poor conditions for comparing results across studies as well. The American studies who utilized SafeGraph were able to perform analysis on a much higher granular level due to the SafeGraph CBG and POI frameworks, than for example the European studies who performed analysis on national and regional scales. Perhaps a higher resolution dataset is available in Europe and the small sample of studies from there simple did not register it.

Another concern regarding the digital divide is the difference in access to technology among demographics and the reported bias of the aggregated dataset's sampling and their inability to adjust for skewed sampling practices (Budd et al., 2020; Coston et al., 2021). Underrepresenting vulnerable, older and at-risk groups in these datasets is especially problematic in the light of the finding that these are the same groups who are most likely to get sick from COVID-19 and also most likely to die from the disease (Roy & Kar, 2020). The obvious reason that underrepresenting certain demographics is a problem is that the dataset is skewed, inherently biased and produces inaccurate results. These inaccurate results are especially problematic since we potentially miss vital insights and key information into the mobility of these vulnerable and at-risk groups. It erodes the foundation for implementing NPIs that help and assist those most in need based on mobility data. This cements the importance of increased transparency for big datasets and not forgetting that the digital divide remains.

Another implication from this is that NPIs do not work equally in practice for different demographics and that interventions favor those who are economically stronger. If it can be consistently observed across more studies that low-income and vulnerable at-risk groups in general comply less with NPIs there likely is an underlying issue with the intervention which should be compensated for. As mentioned in the discussion on big data and context, we can only try to explain these things by deploying a heuristic educated guess. From such a position it would make sense to assume that medium-high income areas are more capable of not working for a period of time or holds jobs that provide opportunity for working at home. As opposed to low-income areas that historically are associated with blue collar working class that might predominantly hold service jobs and be classified as 'essential workers'. One study estimated the percentage of the population who was working from home (teleworking) (Lee et al., 2020) and it would be interesting to compare such results with median-income of small enough geographical units to indication if low-income areas do not have the same opportunity to work from home as medium- and high-income areas.

It is apparent that there are multiple levels to the digital divide created by big data. This includes limited access of information based on data providers, limited transparency with datasets and limited access to technology. The potential underrepresentation of at-risk groups within said datasets may ultimately lead to an approach that does not benefit and help those most in need.

## Conclusion

Mobility data collected from smartphone applications undoubtedly served a useful purpose during COVID-19 for serving the rapid need for knowledge and insight which arose when the pandemic became a global phenomenon. The aggregated datasets of mobility data made available by tech companies have helped analyzing the relationship between COVID-19 transmission, human mobility and the effects of NPIs on both. We now know more about how humans move and travel from local to global scale during a pandemic, than we did before, as a direct result of these analyses. Patterns and behavioral phenomena have been identified which may lead to further research, and this benefits mankind when the next pandemic arrives. However, fundamental issues with the transparency of the data provider's methodology on sampling, concerns about the privacy of the aggregation method as a whole and missing consensus and standardization of analyzing these big datasets are placing these studies under scrutiny.

In general, studies found NPIs to decrease mobility and were able to link it to a decrease in COVID-19 transmission. The degree of the NPI's efficacy in reducing mobility were not agreed upon. Furthermore, some exceptions were found where mobility seemingly increased after NPIs were introduced. An implication of these findings were that NPIs potentially harmed vulnerable at-risk groups which were not able to reduce their mobility despite being affected the worst by COVID-19.

The review identified that passive smartphone data can be used to acquire information about population mobility from a national scale down to a fine geographical resolution like the census block group and points of interest. The missing consensus on standardizing vocabulary and metrics makes it difficult to compare results across studies. Furthermore, the sampling methods lack sensitivity with a risk of biased sampling causing skewed representation of demographics which is inherent in the digital divide of technologies such as smartphones in a population.

Using aggregated data with questionable or untransparent methodologies for scientific studies is done out of necessity and does not signify an ideal approach. As such an implication of using aggregated mobility data from tech companies is that we must make several assumptions in the use of these data and therefore also in the conclusions we draw from them. This does, however, not equal that the approach cannot yield useful and positive results for understanding and improving NPIs. As established, the quantitative big data analytical approach to acquiring actionable knowledge to inform decisions comes with the danger of mathematical intimidation, and drawing direct conclusions from data points without contextualizing it can provide relative false insights. This is made clear by the different conclusions drawn on the efficacy of NPIs which has proved to depend on the timing of the NPI implementation relative to the virus's introduction in a population.

NPIs are a preventive measure and must be implemented early to stop introduction of the virus into new populations. If NPIs are not implemented early enough they can serve the purpose of keeping the infection rate at a manageable level where hospitals are not overflowed. The tradeoff between the stringency of NPIs and results must carefully be considered in relation to the potential long-term consequences to mental and physical health and economic damage on societal scale. The studies selected for this literature review cannot inform us on why the phenomena they observe in their data appear. We can heuristically provide educated guesses, but getting real answers require methods beyond studying mobility data in comparison with indicative factors such as age, income or ethnicity that can be applied to geographical units. They can help us understand the amounts of change and variables that affect the change on different geographical scales, but the reason for the variations themselves stays elusive. This is why mobility data is best used in tandem with other methods that can provide us with much needed context.

## Limitations of the Research

The review was performed by a team of one person. This stands as an inherent weakness regarding the ability to validify the literature selection process. It could have been validified by comparing the correlation between the literature selections from two synchronous but independent selection processes.

## Future Research

The content of this literature review is highly concentrated with publication from the USA which leaves gaps in the knowledge as to if the patterns, findings and insights elucidated within are consistent with findings across the world. This would allow for a better understanding if dealing with universal human behavior phenomena or regional occurrences.

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# Appendix

## Appendix 1 – Full Literature Draft

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## Appendix 2 – Literature Inclusion Phases

### ACM

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## Web of science

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## Appendix 3 – Approval of Bibliography

Hej Rolf
Den vedhæftede litteraturliste er hermed godkendt.
Mh
Mette

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**Til:** Mette Skov <skov@hum.aau.dk>
**Emne:** Literaturliste

Hej Mette,

Jeg har vedhæftet listen med litteratur til godkendelse.

Mvh,
Rolf Mahon

Tilføj en billedtekst