

Sensing pedestrian flows for real-time assessment of non-pharmaceutical policy interventions during the COVID-19 pandemic

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Abstract

Introduction

To combat and mitigate the transmission of the SARS-CoV-2 virus, reducing the number of social contacts within a population is highly effective. Non-pharmaceutical policy interventions, e.g. stay-at-home orders, closing schools, universities, and (non-essential) businesses, are expected to decrease pedestrian flows in public areas, leading to reduced social contacts. The extent to which such interventions show the targeted effect is often measured retrospectively by surveying behavioural changes. Approaches that use data generated through mobile phones are hindered by data confidentiality and privacy regulations and complicated by selection effects. Furthermore, access to such sensitive data is limited. However, a complex pandemic situation requires a fast evaluation of the effectiveness of the introduced interventions aiming to reduce social contacts. Location-based sensor systems installed in cities, providing objective measurements of spatial mobility in the form of pedestrian flows, are suited for such a purpose. These devices record changes in a population's behaviour in real-time, do not have privacy problems as they do not identify persons, and have no selection problems due to ownership of a device.

Objective

This work aimed to analyse location-based sensor measurements of pedestrian flows in 49 metropolitan areas at 100 locations in Germany to study whether such technology is suitable for the real-time assessment of behavioural changes during a phase of several different pandemic-related policy interventions.

Methods

Spatial mobility data of pedestrian flows was linked with policy interventions using the date as a unique linkage key. Data was visualised to observe potential changes in pedestrian flows before or after interventions. Furthermore, differences in time series of pedestrian counts between the pandemic and the pre-pandemic year were analysed.

Results

The sensors detected changes in mobility patterns even before policy interventions were enacted. Compared to the pre-pandemic year, pedestrian counts were 85% lower.

Conclusions

The study illustrated the practical value of sensor-based real-time measurements when linked with non-pharmaceutical policy intervention data. This study's core contribution is that the sensors detected behavioural changes before enacting or loosening non-pharmaceutical policy interventions. Therefore, such technologies should be considered in the future by policymakers for crisis management and policy evaluation.

Keywords

smart statistics; experimental statistics; smart cities; big data; sensor data; SARS-CoV-2; data linkage; decision-making; official statistics; digital surveillance data; digital epidemiology

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Introduction

Using sensor data to develop real-time indicators for official statistics is currently an active field of research within National Statistical Offices (NSIs) and in disciplines such as the social sciences [1–5]. Several pilots and applications to integrate big data, including sensor data, in statistical production have been developed and conducted within the last years. These included job vacancies, enterprise characteristics, smart energy, tracking ships, financial transactions, earth observation, mobile networks, and tourism statistics [6, 7]. Compared to survey or administrative data, the added value of sensor data is the accuracy of the measurements and its potential timeliness [8, 9]. The COVID-19 pandemic has shown that NSIs and social scientists have a central role in providing accurate and timely information required by policymakers during the pandemic [10, 11]. Such required information can consist of monitoring and assessing the impact of policy interventions, which are recurrent challenges for policymakers and governmental bodies [12–14]. During the COVID-19 pandemic, governments introduced several policy interventions with varying strictness (based upon the development of the pandemic) to contain the spread of the SARS-CoV-2 virus. In this pandemic, a wide range of technologies was available to monitor human behaviour [15, 16]. These circumstances offer the unique opportunity to monitor and assess the effectiveness of policy interventions during a crisis using sensor technologies. Therefore, it is particularly relevant for NSIs to analyse this information to further develop the research field of real-time indicators in official statistics. This paper analyses a novel spatial mobility dataset containing pedestrian flows measured by location-based sensors in 49 metropolitan areas at 100 locations in Germany during the introduction and relaxation of several pandemic-related policy interventions. As we will explain, such systems have advantages over using data from population surveys or mobile phones and thus serve as a valuable additional data source. It will be demonstrated that such a system has the potential to be used as a real-time measurement system for assessing the impact of non-pharmaceutical policy interventions. In addition, we will reflect on how using sensor data can be of further relevance for policymaking to better understand the link between policy measures and human behaviour in a crisis, and we will discuss potential data-linkage applications using this specific sensor data.

Background

With the spread of the COVID-19 pandemic, countries worldwide began to implement non-pharmaceutical and pharmaceutical policy interventions to mitigate the transmission of the virus SARS-CoV-2. Our study focuses on non-pharmaceutical policy interventions. About one and a half years after COVID-19 was declared a global pandemic, several studies on non-pharmaceutical policy interventions and their effectiveness in reducing key pandemic indicators, such as growth rate, incidence, or the R-indicator, have been published. Here, we summarize some of the key findings of several recent studies. Although the studies differed in data and methods used, it was overall shown that lockdown periods, school/university closures, closing workspaces,

physical distancing, and closing (non-essential) businesses were highly effective non-pharmaceutical policy interventions reducing the virus transmission. Some inconsistent findings are reported for public transport closure, testing, contact tracing, and (international) travel restrictions. The effectiveness of, e.g. public information campaigns, restrictions on internal movement, or restrictions on public transportation was not conclusively clarified [17–25]. Currently, the most appropriate tool to quantify the severity of non-pharmaceutical policy interventions seems to be the Oxford Covid-19-Government Response Tracker [26, 27], which we will use in our study (for details, see section Policy intervention data). To study how populations have reacted to these interventions during the pandemic, population surveys or data generated through mobile phones have often been used. In the following, the challenges and limitations of these data sources will be outlined and compared to the sensor-based real-time measurements presented in this paper.

Population surveys were used worldwide to collect data on adopting pandemic-preventing policy interventions [28–33]. Because person-to-person transmission causes the spread of SARS-CoV-2, face-to-face surveys were ineligible [34, 35]. Therefore, web surveys were used because no interviewers are required. Furthermore, web surveys represent low costs, short fieldwork periods, and timeliness of the data [36]. However, the use of (web) surveys has several problems in evaluating policy interventions for pandemic-preventing behaviour. First, reported and actual behaviour might differ due to social desirability [37]. Second, memory errors can lead to a bias in the responses [38]. Third, the time gap between interviews and publication hinders a quick assessment of policy interventions. Fourth, the data collection for continuous monitoring is costly [39]. Fifth, web surveys yield biased results for behavioural variables regarding health [40–43]. Finally, most web surveys are based upon non-probability samples and thus have severe restrictions regarding population inference [44, 45]. This aspect of web surveys can be considered as their main issue.

Data generated through mobile phones allows the real-time assessment of actual behaviour and does not rely on people's memory. Several studies based upon GPS, mobile phone position data, and specific smartphone applications have been conducted during the COVID-19 pandemic. For example, a number of studies used real-time mobile phone position data to study changes in human mobility behaviour in the USA, China, and Europe [28, 46, 47]. A further study based upon volunteered geographic information (app data), assessed worldwide mobility [48]. Data from companies such as Google or Baidu was used to study human mobility and the effects of policy measures [49, 50]. However, the data used in such studies suffers from self-selection procedures. The required device has to be owned, the application needs to be known by the owner, no privacy concerns should exist, the willingness to participate is a requirement, owners have to activate the required service of the device/application, and the device needs to be carried continuously. It is unlikely that these consecutive steps will yield a random selection of the population [51]. Hence, using data generated through mobile phones (either location-based or app-generated) to describe changes in mobility or evaluate the effects of policy interventions, will exclude specific subgroups of the

population. Additional problems using GPS-generated data are the accuracy and completeness of the data. GPS devices cause problems due to intended or unintended switch-off, delays due to standby mode, battery issues, or the device not being carried [52–54]. Accordingly, the usefulness of smartphone-based technologies to mitigate and monitor the pandemic is still debated [51, 55, 56].

The spatial mobility data measured by the sensors used in this study include location-based measurements of pedestrian flows in different cities and has received little attention in the scientific literature during the COVID-19 pandemic (e.g. [57]). The recorded data of such systems has several advantages compared to those previously described. First, in contrast to population surveys, these sensors provide objective in situ measurements of the population's behaviour, overcoming problems due to survey respondents' social desirability and memory errors. Furthermore, the delay between recording and reporting results and costs for continuous monitoring are negligible when analysis can be done promptly. Second, in contrast to data generated through mobile phones, an important difference is that these sensors measure only whether public places or locations are still visited, i.e. they do not measure who has visited them. As such, data privacy and protection, which were not always adequately addressed during the pandemic [58], are no issue when using such data. Coverage and selectivity issues in smartphone usage among the population or the required use of specific smartphone applications can also be neglected. Finally, data obtained through such objective in situ measurement systems offers the potential for official statistics output. More specifically, given the number of advantages mentioned and the results provided by this paper, this type of technology and the data collected could be more widely used by NSIs and policymakers, for example, future crisis management or policy evaluation. Until now, only a few applications of such data in official statistics can be found, such as the recording of traffic with traffic loop data [8, 59] or the use of real-time indicators based upon publicly available streamed traffic camera images to monitor busyness during a lockdown [60].

Methods

First, we will describe the sensor and policy datasets used in the study. Second, we will explain the applied methodologies and analysis.

Sensor data

The data of sensors measuring pedestrian flows in metropolitan areas is provided by the company *hystreet.com GmbH*. The data collection started on 01.05.2018 at 27 locations in Germany. The sensor network has been continuously expanded, and currently, sensors are installed in 74 cities at 152 locations in four European countries (Germany, Austria, Switzerland, and the Netherlands). Sensors were installed strategically at these locations from a real estate perspective. A real estate perspective is to determine the possible turnover potential of a location, assess the location quality of the real estate object, and evaluate the attractiveness of cities. As a result, the sensors are located

at centres of metropolitan areas on economically relevant and highly frequented streets and places. According to the definition of the German Federal Office for Construction and Regional Planning, 45 out of 49 analysed cities can be considered metropolitan areas ($\geq 100,000$ inhabitants). The remaining four cities are medium-sized cities ($\geq 20,000$ up to 100,000) [61]. The different sizes of the cities are not taken into account in the analysis, given the majority belong to the same category (metropolitan area), and given that Brocker and Klingwort showed that the developments in pedestrian flows were comparable across cities [62].

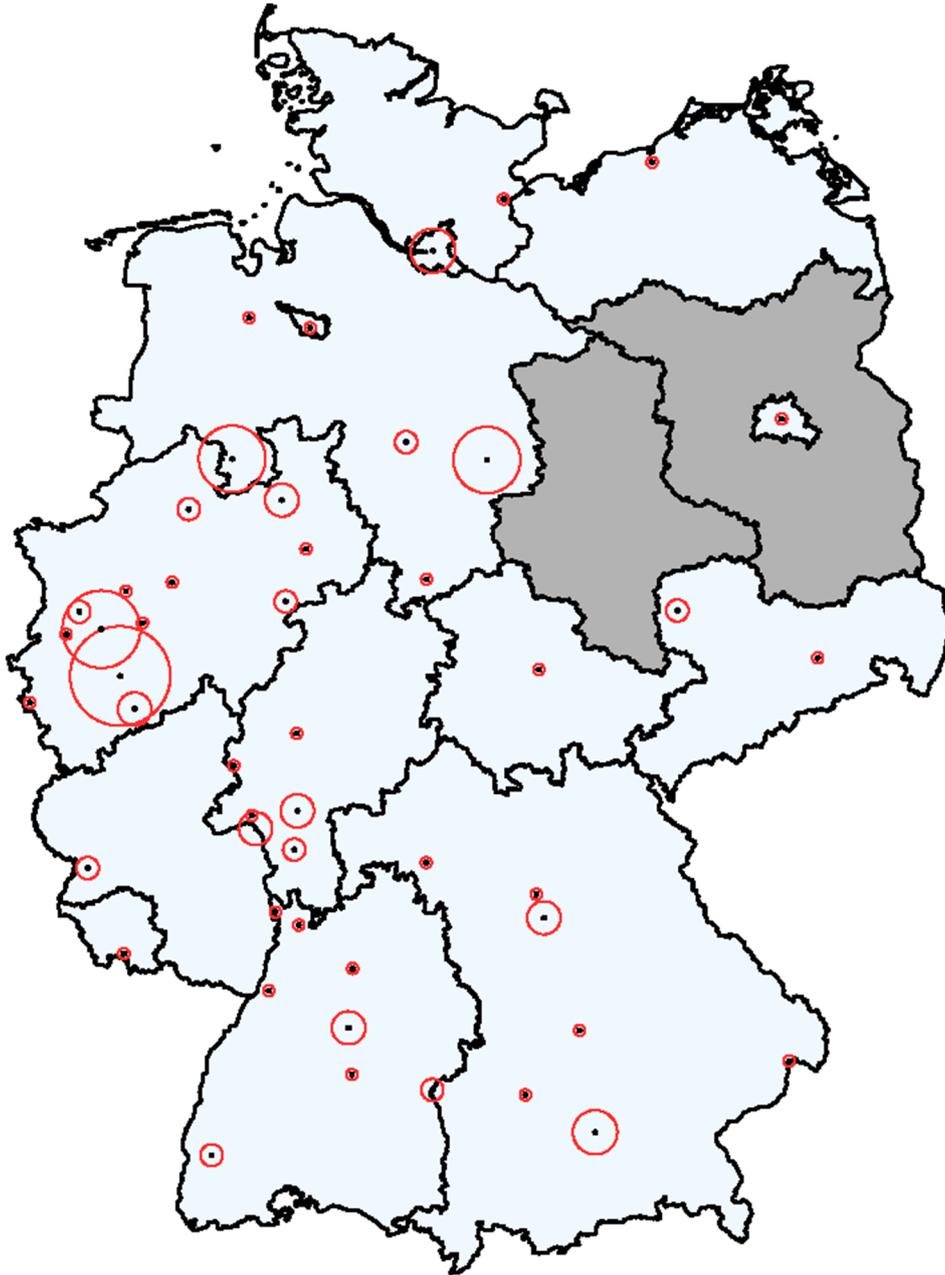
The sensors are attached to facades and generate an invisible and eye-safe quadruple light curtain to measure the pedestrian flows constantly. Hence, pedestrians are not aware of being recorded and cannot consciously avoid the recording. When pedestrians cross the light curtain, a record is made. An accuracy of 99% can be achieved up to a flow rate of approximately 500 persons per minute. Persons crossing the light curtain multiple times are recorded repeatedly. Hence, the total count per day might not be a count of unique persons. For example, persons on their route to, e.g. essential shopping and back, might cross the light curtain twice if they take the same route. However, it is reasonable to assume that such scenarios do not systematically upward bias the pedestrian counts. Only if persons cross the light curtain, in the most extreme case, in the form of a curved line, a form of systematic measurement error will occur. This scenario seems unlikely as people are not aware of the light curtain. Measurement errors can occur if the laser is blocked (e.g. by scaffolding, cranes, or treetops), and in case of energy failure, no measurements are made [63]. When these types of measurement errors occurred, data was excluded from the analysis, as we will explain in the following paragraph.

Data from 01.01.2019 to 18.04.2021 of German sensor locations will be used for the analysis. Sensors with either considerable down-times (about one year) or down-times of at least about three weeks in the periods of interest were excluded from the analysis. The resulting dataset consists of 49 cities with 100 sensor locations. The cities have a minimum of about 25,000 inhabitants, on average about 400,000, and a maximum of 3.7 million (Berlin, capital city of Germany). Figure 1 shows the considered cities and indicates the number of sensors per city. On average, there are two sensor locations and a maximum of nine per city. 14 out of 16 federal states have at least one sensor location because one has no sensors installed and the second is omitted due to the selection criteria.

Policy intervention data

On 11th March 2020, the World Health Organization (WHO) declared COVID-19 a pandemic [64]. After that, policy interventions were enacted, extended, relaxed, or reintroduced in Germany at 15 points in time (in the period considered in this paper). Since the interventions aimed to reduce the number of social contacts, it is reasonable to assume that closing schools, universities, (non-essential) businesses and restricting public gatherings affect pedestrian flows at public places. To quantify the stringency of the measures, we used the 'stringency index' from the Oxford Covid-19-Government Response Tracker (OxCGRT) project [26, 27]. This project systematically records policy measures in over

Figure 1: Sensor locations in Germany



Black dots indicate city centres. Red circles surrounding black dots indicate the number of sensor locations within the 49 cities. Grey-coloured federal states do not contain sensor locations.

180 countries that governments have implemented since 1st January 2020, to address the pandemic. The stringency index has been calculated since 21st January 2020, and consists of 9 indicators recording the severity of lockdown style policies (school closures, workplace closing, cancel public events, restrictions on gatherings, public transportation, stay at home order, restrictions on internal movement, international travel controls, public information campaigns) that primarily restrict people's behavior [27]. Most of these policies were considered highly effective in mitigating the transmission of the virus SARS-CoV-2 (see section "Background"). The stringency index is calculated using all ordinal containment and closure policy indicators, plus an indicator recording public information campaigns. The index ranges from 0-100 (100 = strictest). Table 1 shows the dates when policy interventions were

enacted, describes the interventions, and shows the stringency index on that specific day.

Policy interventions and pedestrian counts

First, we focus on the period from 01.01.2020 to 18.04.2021, which contains 15 points in time with policy interventions (see Table 1). For this period, policy interventions were linked to the pedestrian flow data using the date as a unique identifier. This allows observing potential changes in pedestrian flows before or after interventions. Within this period, 0.1% of the observed data contained zero counts. The sensors store a zero-count in case of a measurement error and for the actual absence of individuals. However, zero-counts on a given

Table 1: Timeline of non-pharmaceutical policy interventions in Germany between 13th March 2020, and 22nd March 2021

No.	Date	Policy intervention and description	Stringency index
1	13.03.2020	Closing schools until May 2020 [65, 66] and universities until summer 2021 [67, 68]	33
2	22.03.2020	Closing of non-essential businesses; restricting public gatherings [69]	77
3	15.04.2020	Extending interventions until May 2020 [70]	77
4	04.05.2020	Stepwise re-opening of schools [71]	72
5	06.05.2020	Opening of a majority of non-essential businesses; allowing limited public gatherings [72]	66
6	02.11.2020	Closing of non-essential businesses (wholesale/retail businesses remained open); restricting public gatherings [73]	62
7	01.12.2020	Extending interventions; increasing restrictions of public gatherings [74]	68
8	14.12.2020	School closings until January 4, 2021 [75]	68
9	16.12.2020	Closing of non-essential businesses (wholesale/retail businesses as well); restricting public gatherings [76]	82
10	04.01.2021	Stepwise re-opening of schools [77]	82
11	05.01.2021	Extending interventions from 16.12.2020 [78]	85
12	19.01.2021	Extending interventions from 16.12.2020 [79]	83
13	10.02.2021	Extending interventions from 16.12.2020 [80]	83
14	03.03.2021	Stepwise re-opening non-essential businesses (incidence-dependent) [81]	78
15	22.03.2021	Extending interventions from 03.03.2021 until 18.04.2021 [82]	75

day are implausible, even in the case of a strict lockdown or an evening/night curfew. Therefore, a conditional median imputation was applied to correct the zero counts.

Pandemic and pre-pandemic pedestrian counts

Second, the period from 01.01.2019 to 31.12.2020 is considered to quantify differences in pedestrian counts between the pandemic (01.01.2020 to 31.12.2020) and the pre-pandemic year (01.01.2019 to 31.12.2019). A complete time series of sensor data is required to calculate the relative difference between 2020 and 2019. As the sensors were installed consecutively over time, the complete time series for 2020 and 2019 were only available for 20 cities and 40 locations. Within this period (01.01.2019 to 31.12.2020), 0.6% of the observed data contained zero counts. These were corrected using the method explained above. Due to the weekday shifts of the same date between years, leap year, public holidays on different weekdays, the pedestrian counts of each location were summed per corresponding city and week. No decomposition of the time series into its systematic and unsystematic components was done. Therefore, we cannot tell whether the pedestrian counts might depend on seasonal influences. The relative difference between 2020 and 2019 is calculated using the 2019 data as the benchmark. Accordingly, a positive relative difference indicates the counts in 2020 being larger than in 2019, and vice versa, a negative relative difference indicates a lower count in 2020 than in 2019.

Results

Policy interventions and pedestrian counts

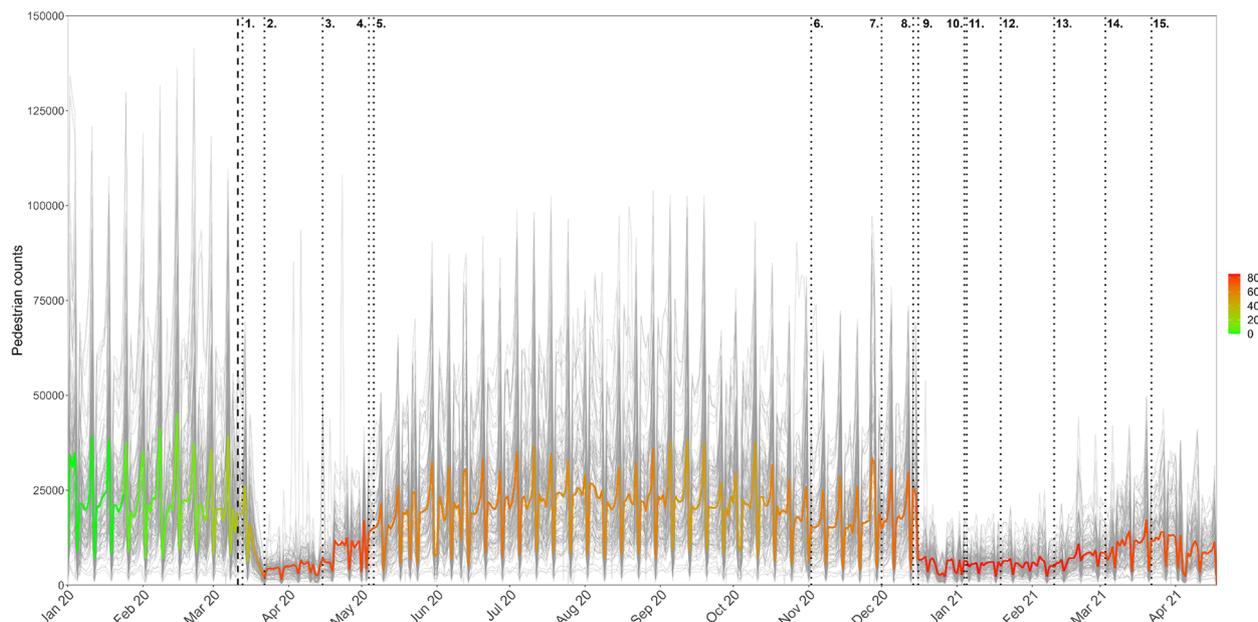
Figure 2 shows the pedestrian counts of all considered cities and locations and the average daily count in the period

from 01.01.2020 to 18.04.2021. In general, the counts from Mondays to Thursdays are comparable, rise on Fridays, peak on Saturdays, and reach the lowest level on Sundays. In Germany, there are peculiarities regarding the opening of stores on weekends. On Sundays, the drop in pedestrian counts is due to almost exclusively to all shops, including essential businesses, being closed. Exceptions include train stations, gas stations, bakeries, restaurants, cafes, and pubs. However, the latter three would have been closed in the pandemic year during a lockdown anyway.

Until early March 2020, a similar and repeating pattern in the pedestrian counts is observed. Shortly after the WHO declaration on March 11th, 2020, pedestrian counts started to decrease. Here, at the same time, the stringency index started to increase. On March 13th, 2020, the first national policy interventions (school closings) were enacted.

The pedestrian counts decreased further before the second policy intervention on 22nd March 2020, when non-essential businesses closed. During the following period, pedestrian counts remained low, although some days show high pedestrian counts at a few locations. Throughout this period, the stringency index increased further. The pedestrian counts started to increase slightly before the interventions were lifted on 4th and 6th May 2020. This finding suggests that behaviour already changed before the policy interventions were lifted. Thereafter, pedestrian counts increased and remained stable during the summer months. Here, the stringency index indicates lower severity of policy measures. After the introduced interventions on 2nd November 2020, almost no decrease in pedestrian counts was observed. A reasonable explanation might be that wholesale/retail businesses remained open, which are likely to be located in the areas around the sensor locations and still attracted customers. With the introduced interventions on 14th and 16th December 2020, a substantial decrease in pedestrian counts was observed. This development is accompanied by a steep

Figure 2: Pedestrian counts in 49 German cities at 100 locations between 01.01.2020 and 18.04.2021



Grey lines show recordings of each sensor. The gradient-colour line shows a) the average daily count, and b) indicates the stringency index (green = low index score, red = high index score). The vertical black dashed line indicates the WHO declaration. The enumerated vertical black dotted lines indicate a point in time with a policy intervention (enumeration corresponds to Table 1).

increase in the stringency index. During these interventions and their threefold extension, the pedestrian counts remained at a low level and the stringency at a high level. An increase after the stepwise re-opening of schools on 4th January 2021, could not be observed. From 1st March 2021, with gradual openings and relaxations, slight increases in pedestrian counts were recorded.

Pandemic and pre-pandemic pedestrian counts

Figure 3 shows the weekly relative difference in the pedestrian counts between the pandemic (2020) and pre-pandemic (2019) year. On average, the pedestrian counts were lower in the first week of 2020 compared to 2019 (-1%). Between the second week up to the sixth week (beginning of February), the average pedestrian counts were larger in 2020 than in 2019 (from 2% up to 13%). From the sixth week, the average pedestrian counts fall below the level of 2019. The pedestrian counts are beginning to decrease in 2020 before the WHO declaration and first policy interventions in week 11 compared to the previous year.

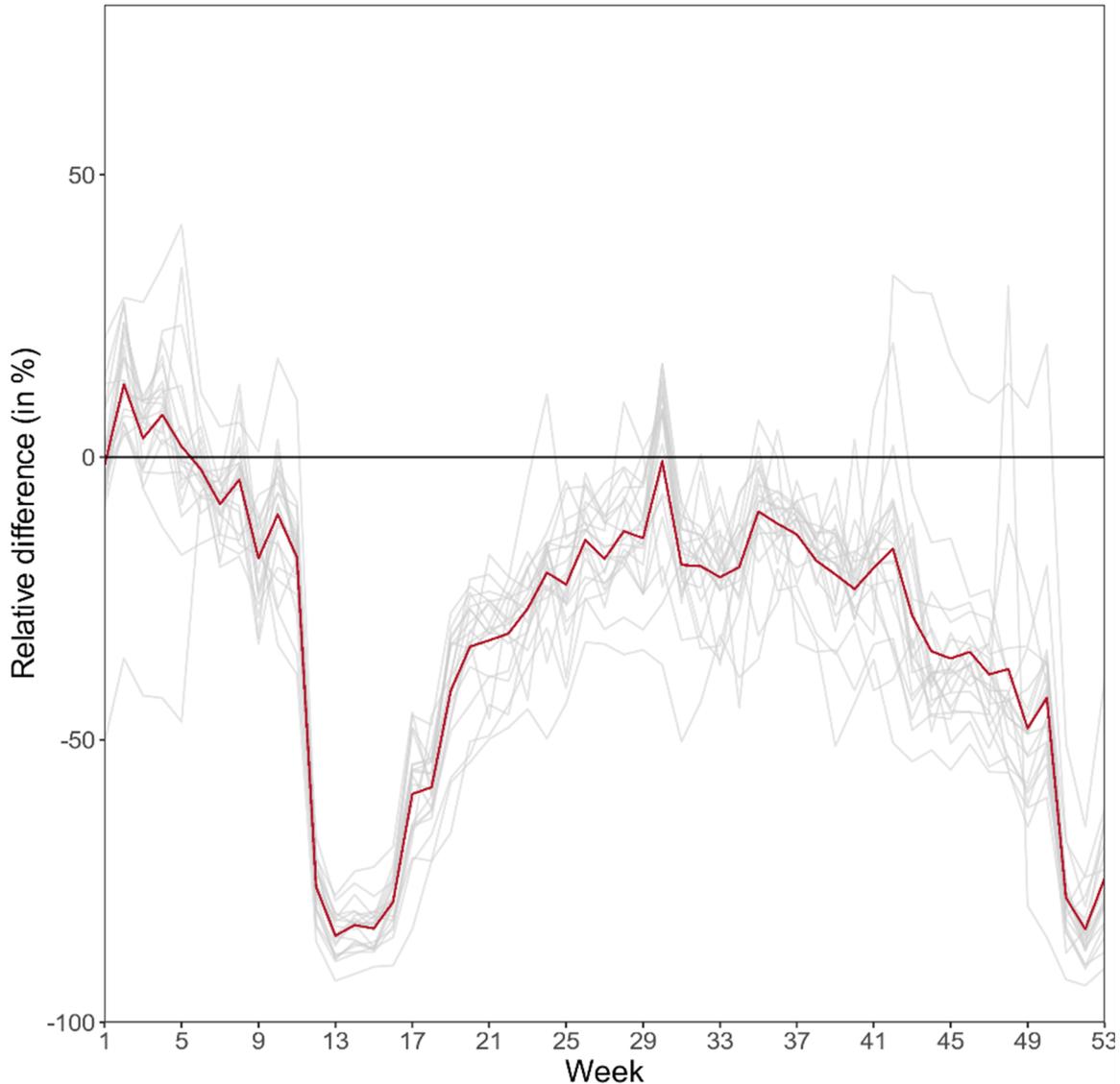
The most considerable difference was observed in week 13 (-85%), the second week after the first restricting policy interventions. The difference remained stable between weeks 13 to 15 and steadily decreased from week 16 (second half of April). Hence, pedestrian counts developed towards the previous year's count about three weeks before the policy interventions were relaxed in week 19. In the following weeks, the average difference converged further to the level of 2019 but remained lower. The difference was positive at some specific locations, i.e. the pedestrian counts were larger at these locations in 2020. In week 30 (end of July), the average difference was about zero. Until week 43, there was some variation in the relative difference (from -14% up to -23%).

Starting in week 43 (second half of October), the average difference started to increase again. Hence, before the policy interventions in November and December 2020, the pedestrian counts started to decline again compared to 2019. By the end of 2020 (weeks 51 to 53), the relative difference was comparable to weeks 13 to 16 (-74% to -83%). A reasonable explanation for this observation might be the same type of policy interventions (see Table 1).

Discussion

This paper analysed sensor-based spatial mobility data of pedestrian counts in 49 metropolitan areas at 100 locations in Germany during a phase of non-pharmaceutical policy interventions due to the COVID-19 pandemic. Furthermore, differences in pedestrian counts between pandemic and pre-pandemic periods were studied, and several observations were made. First, we observed behavioural change and a reduction in counts detected by the sensors that pre-empted restricting policy interventions. Inversely, sensors detected an increase in pedestrian counts before the loosening of policy restrictions. Second, with less strict policy interventions, no considerable reduction of pedestrian counts compared to strict interventions could be observed; a finding consistent with the stringency index. Hence, a decrease in pedestrian counts was always connected with an increase in the stringency index (more severe non-pharmaceutical policy interventions). Third, after the interventions in 2020, on average, up to 85% lower pedestrian counts were found compared to 2019. The findings in this study show the potential and practical importance of sensor systems and corresponding data for measuring real-time behaviour.

Figure 3: The weekly relative difference between pandemic (2020) and pre-pandemic (2019) pedestrian counts in 20 German cities



Grey lines show weekly relative difference per city, the red line shows the weekly average overall cities, and the black solid horizontal line indicates a zero difference.

We consider this research of high importance because, until now, such objective in situ real-time measurement systems recording spatial mobility have been rarely used in the pandemic to evaluate or improve policy decisions. Thus, it highlights the potential of such systems for policymaking. If NSIs would administer such sensor systems themselves and allocate them randomly over a country, ensure quality and usability, such systems could be considered an additional data source for various official statistics [83]. These objective measurement systems are not reliant on adoption by citizens [84], and therefore, do not introduce selection bias due to usage or ownership as mobile phones do. Additionally, such systems do not collect individual data, and accordingly, data confidentiality and privacy regulations are no major concerns. We see great potential and need for such objective measurement systems at NSIs for several applications (e.g. real-time monitoring of the de facto population) and statistical output. For applications during a pandemic or crisis,

such spatial mobility data can be integrated into real-time dashboards [85, 86], along with (non)-pharmaceutical policy interventions, pandemic-related information, and could allow data visualisation on the national or federal-state level to identify regional differences [87]. Targeted policy interventions could be enacted based upon this information bearing in mind that contact tracing is not possible due to the non-identification of individuals.

Furthermore, such spatial mobility data has the potential to be used within data-linkage applications. However, the linkage on the micro-level (individuals) is impossible. Instead, the timestamp or a combination of the timestamp and regional identifier (e.g. city or federal state) can be used to link the pedestrian count data to survey or administrative data. When linked to survey or administrative data, it can be used as auxiliary information to improve existing estimation processes (e.g. using aggregated weekly/monthly counts as auxiliary information when estimating weekly/monthly

economic activity) to help local authorities understand human behaviour as a driving force for societal change [11]. When linked to survey data, it can be used to compare external sensor measures and reported pandemic-prevention behaviour [62]. Additional examples can be safety monitoring in cities, the commercial viability of businesses, or tourism and mobility statistics. When data from different sensor systems is combined, e.g. traffic and air pollution in busy high streets, awareness of health risks can be addressed [88]. The concept of linking data sources, also on the individual level, for more insights and quality improvements of official statistics or in the health sector is currently an active field of research and has already been successfully demonstrated [89–95].

Besides several advantages, there are limitations to this study. The sensors are not distributed randomly over Germany. The stations are located only in metropolitan areas at economically relevant and highly frequented locations and data is not available for all federal states. As a result, no valid design-based inferences could be drawn using this data which is a central demand in statistical production at NSIs. The analysis conducted did not acknowledge the non-random and unequal distribution of the sensors. Therefore, an inference framework would have to be developed, which is considered a research project in itself (see for example [96]). Furthermore, the sensors only provide information about the number of movements (which may not correspond with the number of persons) at the position at which they are installed. The trade-off for this privacy-ensuring measurement limits the number of addressable research questions. For example, relevant questions for policymakers on the demographic composition (e.g. age, gender, occupation) of pedestrians during the pandemic cannot be answered with such data. Using such data for general population studies will be complicated because the sensors miss certain parts of the population. For example, those who are not mobile or have certain demographic characteristics are more or less likely to visit these locations. In addition, the small number of sensors cannot measure the avoidance of public places and the evasion by citizens to other parts of the cities. Moreover, without comprehensive areal coverage, malfunctions of individual sensors have a large impact on the data quality. Furthermore, we did not deduce from the data whether the behavioural change was due to expected policy interventions or perceived risks. However, the data seems to suggest that behaviour preceded policy interventions. Finally, we did not control for external factors (e.g. weather) and did not apply seasonal adjustments (e.g. public holidays or holiday seasons), to control for differences in pedestrian counts. Accordingly, future research will be dedicated to studies on causal inference for policy evaluation and on the control of external factors.

Conclusion

The COVID-19 pandemic has shown that measuring human behaviour during a health crisis in real-time is of high importance. Real-time data for crisis management will continue to be important for policymakers, not only at the national level but also to react in an internationally coordinated manner. Differences in policy measures between countries pose a risk to effective policy interventions across

borders. However, the pandemic has not only been a health crisis but also highlighted sociological challenges. Behavioural and social changes are essential to tackle such a crisis and are, at the same time, the most challenging to change, control, and measure. Hence, tackling such global crises is primarily a social and not a technical problem and cannot be managed solely with technical solutions. The pandemic has revealed challenges, opportunities, and potential for improvement in crisis management in the future, for example, climate change and energy provision. To allow and evaluate crisis management and related policy interventions, the future relevance of measurement systems that records societal changes in real-time will only increase.

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Statement on conflicts of Interest

None declared.

Ethics statement

Ethical approval was not required since no personal data was used.

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Abbreviations

NSI: National Statistical Institute
 WHO: World Health Organization

Additional Notes

The views expressed in this paper are those of the authors and do not necessarily reflect the policies of their affiliations.

The sensor data used in the study can be requested and downloaded at hystreet.com GmbH.

The data of the Oxford Covid-19-Government Response Tracker can be downloaded at <https://github.com/OxCGRT/covid-policy-tracker>



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