Is the multimodality related to urban mobility changes during the pandemic?

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Abstract

COVID introduced new considerations and changed the urban mobility ecosystem and perception. During the pandemic, mobility patterns change according to several factors. Few studies have investigated the impact of the mobility system features on the dynamic of people during the pandemic. This research attempts to understand the relationship between the urban mobility system advancement and the behaviour of people throughout different stages of the pandemic. This study uses big data for day-to-day mobility in different regions in Germany and employs the correlation coefficient matrix to analyze the impact of the smart mobility indices on the trends of mobility and the number of contacts between people. The study covers the whole pandemic period, from 2019 to mid-2022, to derive a pandemic crisis travel mobility patterns for each wave. Overall, a negative correlation between developed mobility systems and mobility trends means that the smarter cities and regions have, the fewer people tend to travel; the second wave marks the greatest mobility decline in correlation with more advanced mobility systems. While sophisticated and advanced mobility systems are often cited as having more attractiveness and a positive effect on the traveller's satisfaction, our findings suggest no clear and discernible impacts during the pandemic were observed. On the contrary, more multimodal trips, sharing options, and smarter mobility, in general, were associated with less mobility of people, yet it does not interfere with the contact between people, during the different stages of COVID in Germany.

Keywords: *Urban mobility, Multimodality, COVID-19, Mobility trends, Smart mobility index, individual contact*

INTRODUCTION

The coronavirus disease (COVID-19) that started at the beginning of the year 2020 has significantly disrupted people's daily life and forced governments worldwide to rapidly enact several restrictions to face the associated health emergency (Wilder-Smith, 2020). The German government, likewise (Jaekel, 2022), established various limitations to flatten the contagions curve. The impact on Urban mobility was evident, but it took a while to identify suitable approaches and strategies to mitigate the spread of the virus, protect the population and maintain a balanced urban mobility system.

The way people move, their mobility choices, preferences, and priorities have significantly reformed: With the social distancing restrictions, people preferred private car usage over public transportation, home office, and online schooling swiped off the need for some of the most frequent daily trips in the urban realm (Kellermann et al., 2022), by the post-pandemic, new habits were

developed, such as online purchase and delivery services (van Hassel & Vanelslander, 2022), consequently less shopping and market-related trips.

In the following parts, we will quantify the mobility of people in Germany its trends and investigate their association with other factors, mainly the level of development of the urban mobility system and, assess the interaction between people and measure their contacts.

LITERATURE REVIEW

The pandemic has led to a general decline in urban mobility worldwide (Linares-Rendón F, 2021) and led to changes and drastic transformations in people's mobility and lifestyle (Palma, 2022). Urban mobility switched to more private cars, fewer shared rides, and much more working from home, decreasing daily trips home to work/school, with low demand for flying and business trips (Karolin Schmidt, 2021). Understanding and quantifying the impact of such a large-scale disruption would be fundamental to help the decision-makers and mobility planners ease the pandemic effects and enhance the resilience for future preparation of similar events. This can be clearly manifested by the amount of related research conducted in this scope (over 12,000 papers[1]).

In this section, we consider only works that have already been peer-reviewed and group them according to how they relate to this work. The eminent studies attempting to investigate the impact of COVID-19 on Mobility by mean of Pearson correlation are not many (Pascale, 2022) used noise sensors data to assess the effect of Covid-19 lockdown on mobility (Tsvetkova, 2022) analyzed the long-term trends on the governance of mobility innovations. Laliotis (2022) investigated how the social interactions related to COVID-19 be associated with mortality in Germany.

Nonetheless, most research has covered very well the spread of COVID with the mobility of people (Shibamoto, 2022), through several methods, like structural modelling (Rafiq, 2022), time series analysis (Zargari, 2022), and activity travel model (Nguyen, 2022). However, there are a few potential problems with not having a study on the mobility advancement impact on people's mobility. First, it is difficult to make informed decisions about how to best support people's mobility during the pandemic without an empirical study. Second, gauging the effectiveness of mobility advancement strategies and how they might be improved can be very challenging without data. Finally, without a targeted analysis, it is not easy to know how the pandemic impacts people's mobility patterns and whether these changes are sustainable in the long term.

Therefore, this research explores the potential impacts of mobility advancement on people's mobility during times of crisis, such as COVID-19, by conducting a correlation study. This study would look at how different factors are involved by employing the spearman correlation analysis, using a correlation matrix for the mobility trends (with five different categories), contacts between individuals, and smart mobility index. Details about the material and the data employed, as well as the methods followed in this paper. Then in the next section, findings and a discussion of the results are presented in terms of correlations between mobility indices, contacts and mobility trends series. Finally, in the last section, findings, conclusion, and further research are devoted to the conclusions.

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[1] Results from sciencedirect, Tandf, Libsearch, and primo, using (COVID impact on urban mobility) on 08.2022

RESEARCH METHOD

The acquisition of large-scale multisource data with high quality is still a high barrier for academic research projects, making them limited and definitive for which kind of research to conduct (Lisha Ye, 2021). Despite the availability of enormous volumes of continuously generated and open-source data, they are usually limited to particular research scopes and periods (Wiltshire, 2022). To make a solid empirical study of urban mobility, the ideal solution would be multi-sourcing data within the same observation period, which is extremely difficult. The data on mobility trends were extracted from Google Mobility Reports, the smart mobility index from the Bitkom reports and the contact between individuals was extracted from a German mobile phone operator dataset using decomposition techniques. In the following part, we will explain the different data sources and how it was processed and analyzed.

1. **COVID-19 Community Mobility Reports – Google**

    CMR data is provided as a comma-separated values (CSV) file comprising over 135 countries, some of which are further detailed on a regional level. It is collected from users who willingly enable their location history and is anonymized as described in (Aktay, 2020). CMR per-locality data comprises six-time series, one for each place category created by Google, given in Table 1. Each time series currently spans over one year, from February 15th to December 31st, 2020, for the first year, and January 1st 2021, to December 31st 2021, for the second year. For a single timestamp and category, the given value is computed relative to a baseline, namely the median value, for the corresponding day of the week, computed for the period between January 3rd, 2022, and February 6th, 2020 (Google, 2020).

    The data shows how visits to places are changing in each geographic region in Germany (Baden-Wurttemberg, Bavaria, Berlin, Brandenburg, Bremen, Hamburg, Hessen, Lower-Saxony, Mecklenburg-Vorpommern, North Rhine-Westphalia, Rhineland-Palatinate, Saarland, Saxony, Saxony-Anhalt, Schleswig-Holstein, Thuringia) over two years (2020,2021 and mid-2022), changes for each day are compared to a baseline value for that day of the week. The baseline is the median value, for the corresponding day of the week, during the five weeks.

Table 1. Place category descriptions from Google CMR (Google LLC, 2020)

Category	Places
Retail and recreation	Restaurants, cafés, shopping centres, museums, libraries, and cinemas.
Supermarket and Pharmacy	Supermarkets, food warehouses, farmers markets, food shops and pharmacies.
Parks	National parks, public beaches, marinas, dog parks, plazas, and public gardens.
Public transport	Public transport hubs, such as underground, bus and train stations
Workplaces	Places of work

We use locality-wise calibrated CMR data, which we process through seasonal-trend decomposition. The research period starts from the beginning of 2020 up to mid-2022. To define the extent of each phase, we used the mandatory notification data on SARS-CoV-2 cases in Germany (Schilling, 2021), giving us five different pandemic stages of SARS-CoV:

- The First wave (CW 9/2020, March 2020 -CW 28/2020, July 2020)
- The Second wave (CW 29/2020, July 2020 - CW 5/2021, February 2021)

- The Third wave (CW 6/2021, February 2021 - CW 25/2021, June 2021)
- The Fourth wave (CW 26/2021, June 2021 - CW 37/2021, September 2021)
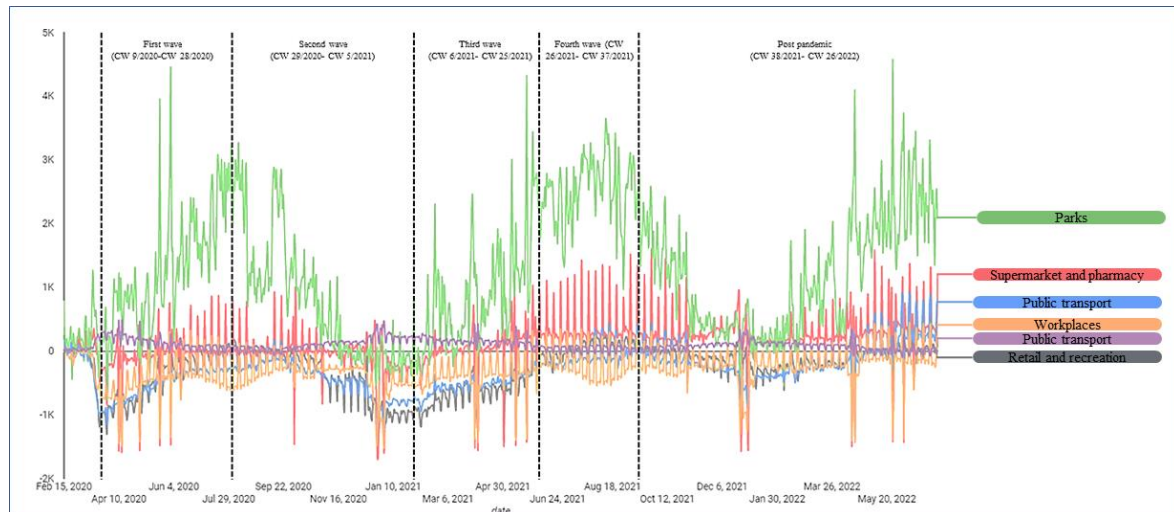- And the post-pandemic period (CW 41/2021, October 2021 - CW 26/2022, June 2022)

Figure 1. Original CMR data for Germany. Vertical dashed lines indicate periods from each COVID-19 wave starts/finishes, from March 2020, until June 2022.

2. Smart Mobility Index

Within Bitkom e.V reports for Smart City Index for 2020 and 2021, the digital ranking of major German cities was explored to inform about the status quo, developments, and trends. With more than 11,000 data points recorded, checked, and qualified, 81 cities with at least 100,000 inhabitants were analyzed and rated in the five subject areas of administration, IT and telecommunications infrastructure, energy and the environment, mobility, and society. The reports give good insights into advancing the overall smart city applications in different cities and regions in Germany (Figure 2). For this study, we focused mainly on the data related to smart mobility, and took the following indices:

- **Parking**: Smart parking, Cell phone parking
- **Smart traffic management**: Intelligent traffic lights, Digital traffic signs, Automated counts
- **Networked public transport**: Cell phone tickets, Real-time information, Free Wi-Fi, Autonomous vehicles
- **Sharing offers**: Car sharing (number of vehicles per 1,000 inhabitants, e-cars), Bike sharing (offer available, e-bikes), Ride sharing (ride pooling, on-demand traffic, Commuter/passenger portal), E-scooter sharing, E-scooter sharing
- **Multimodality**: Multimodal app (offer available, app rating), Mobility stations, Modal split
- **Last mile logistics**: Micro hubs/city hubs, Alternative delivery, Cross-provider parcel stations
- **Further pilot projects**

Data related to the level of mobility as a service has been so difficult to be defined, especially with the different levels of MaaS applied (level 0, level 1) (Daniela, 2020) so that the existence of the system cannot be denied, neither it can be a clear case or a reference for Mobility as a Service. In this study, shared mobility, multimodality and mobility on the transits refer to the MaaS usage on different levels. However, other factors are analyzed likewise and covered with the study on inspecting the mobility trends during the pandemic vis-à-vis the mobility advancement.
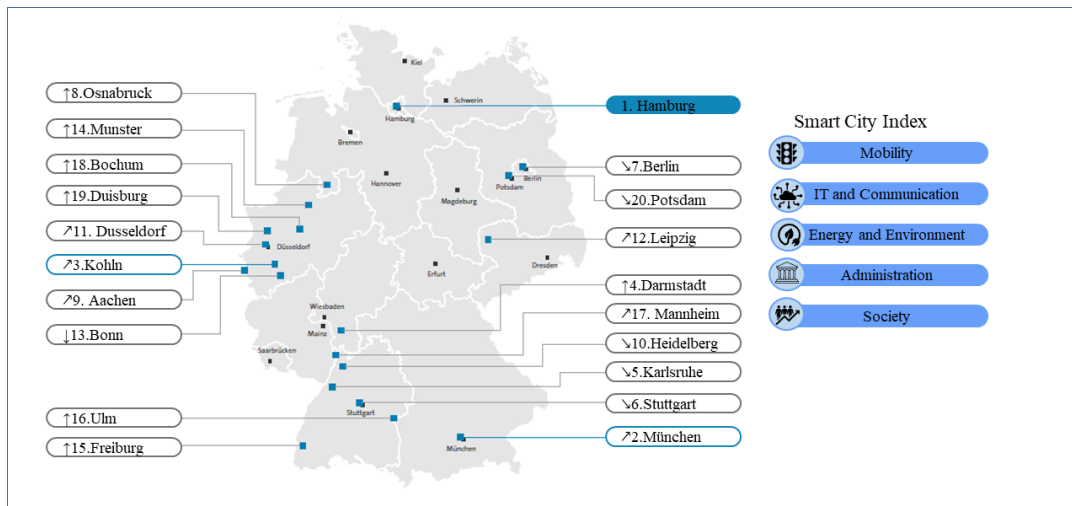

Figure 2. Top 20 Smart City Index 2021, based on data from Bitkom e.V.

3. Contacts Between Individuals

People's modes of transportation can vary, especially with the new modalities of mobility (Luh, 2022). However, it is generally agreed that contact between people is the primary way transmissions occur (Rana, 2022). This is especially true if people share a space for some time (Liu, 2022) where they encounter each other.

This is a very rough measure, as not all contacts are equal in terms of the risk of infection. For example, a hug between two elderly persons, who are not in the same household and do not have any other risk factors (Fields, 2021), is a far less risky contact than sharing a meal with a friend who is infected with COVID-19. The number of contacts, which we can call contact intensity, is an essential parameter in spreading infectious diseases (Liu, 2022). The more contacts, the more likely the pathogen will spread.

GPS, or Global Positioning System, is a technology used to track the location of mobile phones over time and indicates when people are close. Accordingly, it can derive how many contacts a person encounters. The location data are available, provided by the German company NET CHECK from cell phones, but the exact measures are not accessible. We use the number of contacts as a proxy for social life activity, focusing on the number of contacts each day. Around 1.2 million devices (about 50% active every day) in Germany are equipped with a software development kit (SDK) to generate GPS data. All the users were informed and agreed to collect the data (that does not contain personal information) for statistical purposes. Several hundred locations are transmitting per day for each device.

The data for this study is GIS-based; each row is affiliated with a location within the German territory. We classify it by region and associate it with the datasets selected for the mobility analysis, and the datasets are divided into the mentioned categories. We opted for the most relevant trends and indices, and this classification allows as well to recognize better the impact of each factor. Figure 3 illustrates the overall process of the data analysis in this study. Further, Figure 4 shows the Pearson correlation coefficient for each of the five periods, and the graph summarizes the overall average of mobility trends, smart mobility indices and the contact between people.
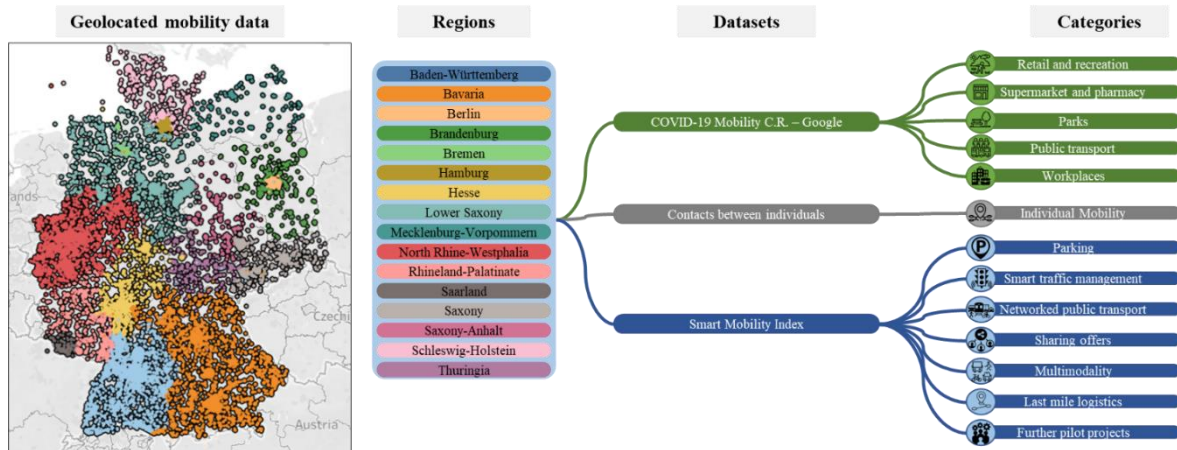

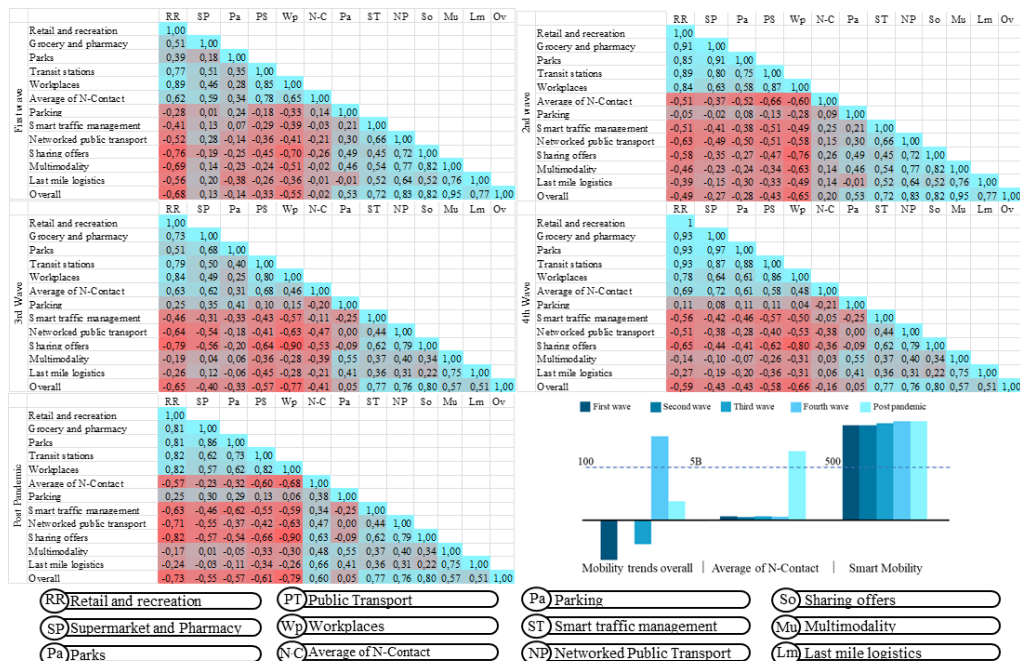**Figure 3.** Process of the data analysis, geolocation, abstraction by region, datasets, and categories.

Figure 4. Correlation matrices for the pandemic stages and the summary of the Mobility trends, average number of contacts, and the smart mobility index for each stage.

Over the five different periods, there was a **negative** correlation between the analyzed variables, except for the contact between individuals. Nevertheless, the overall correlation was different from one period to another, where in the first wave, the average of r is -0,234, and the followings in chronological order are -0,293; -0,321; -0,310, -0,226. The third wave had the overall highest correlation values.

A positive correlation refers to the increase of the mobility of people with the existence of a smarter mobility system, and a positive correlation with the contact between people means the increase in contact with the mobility of people for specific purposes with a well-advanced mobility system. Likewise, a negative correlation suggests that fewer people move with more advanced mobility systems. The contact between people also refers to a less interpersonal connection with an advanced mobility system.

The highest correlations noted in the analysis were within the sharing offers and the Working places, with 0,900 and 0,898 for the post-pandemic and the third wave, respectively. The positive correlation was noted within the number of contact and the transit stations within the first wave; other high positive correlations also were noted within the same period for the Working place and the contact of individuals with 0,65.

No significant relationship was found between the smart mobility indices in general and individuals' contact in the second wave, varying from 0,093 to 0,260. The lowest correlation recorded was 0,008 and -0,016 between the smart parking index and the grocery and pharmacy mobility trends in the first and second waves, respectively.

FINDINGS AND DISCUSSION

The necessity and demand for urban mobility under special circumstances have created the need for researchers, policymakers, and urban planners to better understand user behaviours and travel patterns. In this paper, we examine different types of urban mobility together with different advancement levels of mobility and the way people interact during the pandemic in Germany.

The result of the study suggests that during the Covid time, mobility trends change, in different ways, from one city to another, depending on the advancement of the mobility system. However, the correlation was not strong in most cases, meaning other factors might have influenced the mobility system during this time. We conducted a detailed correlation between the mobility trends (Retail and recreation, Supermarket and pharmacy, Parks, Public transport, Workplaces) and the smart mobility indices (1. Park, 2. Smart traffic management, 3. Networked public transport, 4. Sharing offers, 5. Multimodality, and 6. Last-mile logistics), and the contact between individuals, the results indicated the following:

Cities with more advanced mobility systems have less mobility of people, which does not interfere much with the contact between individuals. This can be associated with the fact that people provided with technologies tend to be less active, especially during the COVID time (Simonian, 2022). Also, the cities with higher smart mobility index managed to implement digital tools to support the public health response to COVID-19, involving case identification, population surveillance, contact tracing, and assessment of interpositions (Budd et al., 2020) which reflected a better response to the rules and measurements and thus less mobility of people.

On the first wave, cities with smarter mobility systems tend to have fewer movements of people to retail and recreation places. Particularly, with more sharing options, less mobility is

noticed to working places. No impact of mobility advancement on the mobility to groceries and pharmacies since such services are essential for any population and under any conditions (Hernandez, 2022). In the post-pandemic, the high negative correlation between the sharing offers and the working place trips suggests that people kept avoiding car-sharing options even after the pandemic, Kim et al. (2022) and Chi et al. (2022) found that customers are less likely to choose sharing economy products under pandemic conditions.

CONCLUSION AND FURTHER RESEARCH

Such a study could provide valuable insight into the potential impacts of mobility advancement on people's mobility during a crisis. The substantial return to public transportation and ridesharing is a necessary but not a satisfactory condition, yet more efforts will be needed to enable a more hygienic shared mode environment. The shift in the behavior of urban mobility users could open new opportunities for more individualized services and options, such as Mobility as a Service, and enable many technologies to take place and play a big role in defining the future mobility picture.

Although the study could uncover several aspects of the relationship between the mobility of people, smart mobility features, and interpersonal contact, a general shortcoming can be derived from the employment of the correlational method, that it can identify associations between exposure and outcomes but cannot identify causes and cannot be taken to imply causation. The research required extensive work and a considerable period to gather, structure, synchronize and analyze immense mobility datasets and derive conclusions with concrete and measurable indices, yet the recent literature suggests more efficient tools such as Machine Learning techniques and advanced Big Data Analytics to handle such topics with less time and more accuracy and capacity to include larger datasets. Despite the limitation of data availability, the research can also be generalized to a larger scale and other countries to reveal more facts and perceive the subject from other perspectives.

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