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Mobility in pandemic times: Exploring changes and long-term effects of COVID-19 on urban mobility behavior

Robin Kellermann [a,*], Daniel Sivizaca Conde [b], David Rößler [b], Natalia Kliewer [b], Hans-Liudger Dienel [a]

[a] Technische Universität Berlin, Department of Work, Technology and Participation, Cluster Mobility Research, Berlin, Germany
[b] Freie Universität Berlin, Department of Information Systems, Berlin, Germany

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ABSTRACT

The COVID-19 pandemic marked a global disruption of unprecedented scale which was closely associated with human mobility. Since mobility acts as a facilitator for spreading the virus, individuals were forced to reconsider their respective behaviors. Despite numerous studies having detected behavioral changes during the first lockdown period (spring 2020), there is a lack of longitudinal perspectives that can provide insights into the intra-pandemic dynamics and potential long-term effects. This article investigates COVID-19-induced mobility-behavioral transformations by analyzing travel patterns of Berlin residents during a 20-month pandemic period and comparing them to the pre-pandemic situation. Based on quantitative analysis of almost 800,000 recorded trips, our longitudinal examination revealed individuals having reduced average monthly travel distances by ~20%, trip frequencies by ~11%, and having switched to individual modes. Public transportation has suffered a continual regression, with trip frequencies experiencing a relative long-term reduction of ~50%, and a respective decrease of traveled distances by ~43%. In contrast, the bicycle (rather than the car) was the central beneficiary, indicated by bicycle-related trip frequencies experiencing a relative long-term increase of ~53%, and travel distances increasing by ~117%. Comparing behavioral responses to three pandemic waves, our analysis revealed each wave to have created unique response patterns, which show a gradual softening of individuals' mobility related self-restrictions. Our findings contribute to retracing and quantifying individuals' changing mobility behaviors induced by the pandemic, and to detecting possible long-term effects that may constitute a "new normal" of an entirely altered urban mobility landscape.

1. Introduction

The confirmation of first cases of the COVID-19 virus in the Chinese metropolis of Wuhan in December 2019 marked the beginning of a globally disruptive period of unprecedented scale. Apart from triggering an immediate public health crisis, the rapid spread of the virus impaired the entire economic and social system by generating a critical state of uncertainty and instability. Across the various domains that were disrupted by COVID-19, human mobility and transportation were among the most affected. As the virus transmits to other individuals through breathing in air that is contaminated with small particles and droplets containing the virus, the ongoing pandemic, alike previous ones (Epstein et al., 2007; Palmer et al., 2007), is inevitably associated with human mobility. This relationship was proven by the spread of the virus evolving into a worldwide pandemic within just a matter of weeks (WHO, 2020), which was facilitated by intense volumes of global air travel and Wuhan's pronounced international accessibility (Musselwhite et al., 2020). Trying to impede or at least decelerate human-to-human transmission of the virus, governments were forced to install drastic countermeasures ranging from travel restrictions to social distancing orders, curfews, quarantines, and the implementation of complete or partial lockdowns, which all were found to have direct or indirect effects on transportation levels and mobility behaviors respectively (de Haas et al., 2020; Abdullah et al., 2020; Bucsky, 2020; Barbieri et al., 2021; Kim and Kwan, 2020). Thus, enforced immobility and isolation were found to be the only correctives to affront a fast-moving virus (Freudendal-Pedersen and Kesselring, 2021). Individuals also adapted their mobility behavior on a personal basis, choosing different

* Corresponding author.
E-mail addresses: robin.kellermann@tu-berlin.de (R. Kellermann), daniel.conde@fu-berlin.de (D. Sivizaca Conde), david.roessler@fu-berlin.de (D. Rößler), natalia.kliewer@fu-berlin.de (N. Kliewer), Hans-Liudger.Dienel@tu-berlin.de (H.-L. Dienel).

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routes or modes of transportation to avoid potential contagion or to respond to changing circumstances in daily movements, such as switching to working from home or homeschooling.

Thanks to the availability of vaccines (albeit unequally distributed globally), the pandemic now appears to be more controllable, and economies seem to be recovering. However, the transportation sector is still facing serious uncertainties regarding the question of whether the pandemic has possibly generated long-term effects on transportation mode choice and peoples' attitudes towards travel (Barbieri et al., 2021) that cause a profound behavioral and thus transportation-economic restructuring. While, for example, the hard-hit air transportation sector is assumed to recover within the next four to six years (Sobieralski, 2020), long-term uncertainties apply in particular to public transportation (Tirachini and Cats, 2020), as various studies highlighted peoples' reluctance to retrieve pre-pandemic public transportation usage behaviors even if the pandemic is under control (de Haas et al., 2020; Przybylowski et al., 2021; Thomas et al., 2021).

Despite the pandemic lasting for more than two years now, the main body of research often focused on a single lockdown period (particularly spring 2020), generating a lack of longitudinal and comparative perspectives that can be complementary to the many profound examinations of singular epidemiological peak periods (Borkowski et al., 2021). In other words, there is a growing need to differentiate mobility-related phenomena induced by COVID-19. However, with only a few longitudinal studies at hand (Kim and Kwan, 2020; Molloy et al., 2021), there is a lack of understanding of the intra-pandemic dynamics, generating insufficient evidence regarding the questions of which modes, if any, return to pre-pandemic "normality" over the course of the pandemic, and of what the potential long-term effects constituting a "new normal" are. Furthermore, there is a lack of understanding of whether mobility behavior is directly related to the various pandemic waves or whether mobility behaviors show a kind of "adaption pattern" that potentially disconnects from the pandemic's actual metrics.

Against this background, the article aims to fill the gap in longitudinal and intra-pandemic assessments by analyzing mobility data from a sample of Berlin residents derived between January 2019 and September 2021. The considered period entails a 20-month pandemic period (March 2020–September 2021) including three epidemiological waves that is contrasted with a pre-pandemic reference period (January 2019–December 2019).

More precisely, there are three research goals. First, the article aims to illuminate the general interrelations of COVID-19 with transportation and mobility by means of a diachronic exploration of how the pandemic affected trip frequencies and traveled distances within Berlin. Secondly, the article seeks to provide statistical insights into modal shifts induced by the pandemic. Thirdly, it aims to differentiate these effects by retracing the intra-pandemic cycles and dynamics by a comparison of transportation-related behavioral responses to the three epidemiological waves. The first wave (March–May 2020) is defined as the initial spread phase of the virus in Germany, culminating in an interim peak of 7,000 new daily infections on 16 March (Robert Koch-Institut, 2022) and the installation of a seven-week lockdown (22 March). The second wave (September 2020–February 2021) is characterized by a tense phase that had exceeded all parameters of the first wave by mid-October 2020 and culminated in a peak of about 34,000 daily infections on 23 December (Robert Koch-Institut, 2022), which led to the installation of a second full lockdown (16 December). The third wave (March–May 2021) characterizes a phase of a renewed rising of incidence rates that started right after a short period of stabilization in winter 2021. Though closely interlocking with the second wave, the third can be distinguished by the emergence of a new virus mutation that resulted in newly rising incidence rates, reaching a peak of about 12,000 daily infections by the end of April (Robert Koch-Institut, 2022) and the start of the vaccination campaign that had reached a 30 % vaccination level by mid-April.

Exploring the longitudinal developments and comparing the wave-specific dynamics is considered critically important for transportation research and policymaking regarding the long-term assessment of COVID-19. As the pandemic is both an enduring and dynamic phenomenon, longitudinal assessments are suggested to provide more credible hints of long-term effects than the analysis of singular lockdowns.

The paper is structured as follows: First, in Section 2, we examine the body of similar or related work on the issue of measuring changes in human mobility behavior as induced by the COVID-19 pandemic. Then, in Section 3, the dataset used in this study is presented, and the analytical methods used in this investigation are explained briefly. In Section 4, the results of the conducted analyses of changes in mode choice behavior during the pandemic period are presented. The results are presented in different levels of aggregation, ranging from general mobility changes (Subsection 4.1) across all modes, to mode-specific changes (Subsection 4.2), and time-specific behavioral responses to the three pandemic waves (Subsection 4.3). Afterward, the results are discussed and contextualized with the limitations of our investigation in Section 5. Finally, in Section 6, we draw overall conclusions from our findings and point out some political implications.

2. Literature review

As a result of the pandemic lasting for more than two years now, we find plenty of empirical evidence of how the virus changed the transportation and mobility-behavioral landscape. Notwithstanding the heterogeneity of studies regarding their respective geographical, temporal, or modal focus, there seems to be consensus in at least the following three key findings: The pandemic induced (1) a decrease in general mobility levels during first lockdowns, (2) a drastic decrease in the use of public transportation, and (3) an increase in individual and active mobility modes.

(1) Decrease in general mobility levels during first lockdowns

When most nationwide lockdowns came into force in March 2020, mobility purposes were reduced to a minimum as schools, workplaces, shops, and cultural facilities were closed. Consequently, total mobility levels plummeted worldwide. A global survey on commuting behavior during the first lockdown revealed that almost 60 % of respondents declared to have fully curbed their previous commuting behavior (Abdullah et al., 2020). The number of trips in Australia decreased by 50 % (Beck and Hensher, 2020), and average trip distances in the US dropped from 40 miles to 23 miles (Lee et al., 2020). About 42 % of respondents in an Indian survey reported to have already fully stopped traveling (Pawar et al., 2020) during the transition to a lockdown phase. In Europe, the most drastic decreases in general mobility levels were observed in Spain (70 %), while Sweden experienced the smallest decrease (about 20 %) (Woskie et al., 2020). Analyzing GPS data in Switzerland, researchers noticed a reduction of around 60 % in average daily distance (Molloy et al., 2021). Interpreting mobile phone data from Germany, a research team observed a 35 % decrease in mobility on a weekly average during the second half of March 2020 (Bohnensteffen et al., 2021). Notably, the latter pointed to the relevance of settlement structures in the context of mobility reductions, as densely populated urban environments experienced more drastic reductions than rural areas.

Accentuating the severity of pandemic impacts on the urban level, a study conducted in the Spanish city of Santander demonstrated that overall mobility dropped by 76 % (Aloi et al., 2020). Moreover, a study on Budapest observed a 51–64 % reduction in mobility during the first lockdown (Bucsky, 2020). In contrast, mobility-behavioral change in rural areas was found to occur far less drastically (König and Dreβler, 2021).

Considering the effectiveness of governmental measures to reduce mobility, mandatory orders (e.g., stayat-home orders, workplace and school closures) were found to account for the largest declines in EU-wide mobility (Woskie et al., 2020). State measures in the UK were found to result in a reduction of driving, public transportation use and walking of 60, 80 and 60 %, respectively (Hadjidemetriou et al., 2020). Similarly, based on analyzing telecommunication data from Japan, a study demonstrated a decrease of up to 90 % of the population density in crowded areas of Sapporo, thus pointing to the effectiveness of governmental measures targeting a reduction of physical exchange during the first lockdown (Arimura et al., 2020).

Retrospectively, people worldwide responded to the initial spread of the pandemic by drastically curbing their mobile activities. However, following the initial shock of the global emergency, suppression of mobility demand resulted in changing mobility patterns, represented by shifting transportation mode choices. These changes comprised two overarching characteristics: (i) plummeting use of public transportation, and (ii) an increase of individual and active travel modes.

(2) Drastic decrease in use of public transportation

From an epidemiological point of view, public transportation is generally considered a critical mode, as many people traveling in close proximity in confined environments increases the likelihood of transmitting respiratory infections (Troko et al., 2011). Consequently, public transportation under COVID-19, like in previous pandemics (Goodwin et al., 2009), was immediately perceived as a risky mode (Tirachini and Cats, 2020) to be avoided as much as possible. Negative public perception, aligned with occasionally reduced services, resulted in public transportation suffering by far the hardest decline in ridership across all modes. For the New York Subway, researchers reported a ridership reduction of 90 % by end of March 2020 (Teixeira and Lopes, 2020). The same relative decline was detected for public transportation use in Switzerland (Molloy et al., 2021). A Spanish research team found the amount of public transportation users in Santander to have dropped by up to 93 % (Aloi et al., 2020). In a study conducted in the Polish city of Gdansk, 90 % of respondents declared to have resigned or limited public transportation usage (Przybylowski et al., 2021). Similarly, public transportation use in Budapest was found to have decreased by 80 % (Bucsky, 2020). According to a comparative global analysis, the most drastic behavioral shifts towards avoidance of public transportation were found in Iran and Australia (Barbieri et al., 2021).

The trend of sparse public transportation use continued also after the end of the first pandemic wave and, despite increasing ridership, often did not reach pre-pandemic levels (Molloy et al., 2021; Jenelius and Cebecauer, 2020). At the same time, overall mobility levels increased during spring and summer 2020, indicating travelers' tendency to substantially reorganize their mobility behaviors.

(3) Increase in individual and active mobility modes

Regaining mobility after the first lockdown was realized by significant shifts to individual and active travel modes, as these were perceived as more comfortable in times of social distancing. Various studies observed an increase in the use of private cars, as well as walking and cycling (Abdullah et al., 2020; Przybylowski et al., 2021). Significant modal shifts to car use were, for example, reported for Germany (Knie et al., 2021), Australia (Beck and Hensher, 2020) and India (Das et al., 2021), and more so for Budapest (Bucsky, 2020), Istanbul (Shakibaei et al., 2021), and the German Hanover Region (Schaefer et al., 2021). Regarding the latter observation, the shift to car use was however found to depend on geographical and socio-economic characteristics, as total car use only increased among metropolitan residents and decreased among residents in less densely populated urban areas.

Concerning active travel modes, a study conducted in the Netherlands noticed an almost doubling of walking trips during March and April 2020 (de Haas et al., 2020). Moreover, a Swiss study (Molloy et al., 2021) demonstrated an intensely increased preference for cycling regarding both the number of trips per day and regarding daily distance traveled in the aftermath of the first lockdown. In contrast, a German study (Knie et al., 2021) observed a growth in bicycle use only in mid-sized cities. Altogether, individual transportation became more important as it served as a compromise to stay mobile while maintaining the provision of social distancing. However, long-term effects of these substitution practices remain unclear.

3. Data & methods

3.1. Data

The central dataset of this study is constituted by mobility data of a sample of Berlin residents collected between 1 January 2019 and 30 September 2021, thus allowing for the analysis of mobility behaviors before and during the pandemic. The 754,493 trips in this dataset refer to voluntary users of two smartphone applications that log all trips and travel modes based on a GPS-based tracking system developed by MOTIONTAG. Both apps serve the purpose of providing users with a detailed analysis of their individual travel patterns for informative reasons and for making trip planning more efficient. These location tracker apps automatically save the GPS tracks on the smartphone in the background and then upload them to the MOTIONTAG analytics platform. On this platform, stages and travel modes are assigned from the GPS tracks, which implies a high spatial accuracy of the data collection. Furthermore, in a study on another sample, accuracy was found to be above 80 % and partly above 90 % for the mode detection algorithm (Molloy et al., 2022). Achieving additional accuracy, app users can validate whether a trip really took place and whether the mode was correctly classified. If necessary, both pieces of information can be corrected and the corrected data and the algorithmic detection are stored in the analytics platform (Molloy et al., 2022). In this work, a trip represents the direct movement of an individual from point A to point B using a single mode of travel. The data generated in this way is available to the authors in anonymized form, which means that no conclusions can be drawn about individual users. Attributes such as "start time", "distance", "duration", and "means of transportation" are provided for each trip. In order to compare the mobility changes at different time periods and to reduce the influence of outliers, single trips and distances are aggregated at weekly, monthly and annual levels. Over the entire observation period, the number of trip-generating users increased continuously, which results in a corresponding increase in the absolute trip count. To ensure that this increase is explained by changes in mobility behavior, the respective user count is added to the dataset for each time period. By setting the total number of trips in a certain time period in relation to the number of users in this period, mobility changes can be examined in a normalized way.

The diachronic analysis of mobility data is contextualized by official infection figures provided by the German Robert Koch Institute (RKI) and is further contextualized by political measures aiming to control the spread of the virus (e.g., full or partial lockdowns).

3.2. Descriptive analysis of mobility changes

The central analytical objective of this study is to describe mobility-behavioral changes over time through the examination of absolute and relative changes of trip frequencies and traveled distances before and during the pandemic. The decision to analyze trip frequencies is based on the assumption that the number of average trips can be considered an indicator for a person's general activity level that provides an abstract insight into changing travel behaviors before and during the pandemic. Moreover, the decision to analyze travel distances is motivated by providing a complementary picture to a person's varying trip frequencies, thus further qualifying travel behavior through unveiling possible changes in the length of traveled distances. Various large mobility studies also set such aggregated individual mobility parameters in relation to a temporal context (e.g., average trips/distances per person per day/week/month/year) for the investigation of mobility changes (see Ecke et al., 2020; Nobis and Kuhnimhof, 2018; Gerike et al., 2018). In the following, mobility is defined as the average number

Fig. 1. Change of monthly trip frequencies (top) and traveled distances (bottom) in the context of weekly COVID-19 infections in Berlin.

of trips or distances per person within a given period. Equation (1) describes the relative changes in average trips or distances per person in a period of the respective means of transportation.

$$V_{M,e} = \left(1 - \frac{\sum_{m\in M; j\in U^l} v^l_{j,m,e}}{\sum_{m\in M; j\in U^0} v^0_{j,m,e}}\right)\cdot 100 \tag{1}$$

Here, M denotes the set of regarded transportation modes and U^i the set of users in period i, with l the period to be compared with the base period 0, and e indicates whether trips or distances are considered. The absolute and relative changes in trips and distances are examined according to the different types of transportation. To analyze the impact of the pandemic on public transportation, we aggregate the modes “Subway”, “Bus”, “Lightrail Train”, “Train” and “Tram” to constitute “Public Transportation”.

However, the modes of individual transportation “Bicycle”, “Car” and “Walking” are considered separately. The two dimensions, trips and distances, can be used to analyze how usage of a mode of transportation changed during the pandemic period. In addition to the absolute and relative change of the different modes of transportation, the modal split is also calculated for each period in this paper. The modal split shows the respective share of a mode of transportation measured by the number of trips to the total sum of all trips in a period. By comparing the modal split with the absolute and relative changes in trips and distances, well-founded statements can be made about the level of change and its influence on overall mobility.

3.3. Inferential analysis of modal shifts

In this work, we use correlation and regression analysis as means to inspect relations between modes of transportation. Furthermore, we want to gauge the extent to which trip frequency and distance traveled in each mode relates to the overall mobility. Since we cannot expect variables to fulfill the requirements imposed by the Pearson correlation coefficient, we employ *Kendall’s rank correlation coefficient* as a measure of association between transportation modes. In addition, as the absence of rank ties cannot be asserted, the rank correlation coefficient τ_b is used, which is corrected for the bilateral presence of ties and is defined as $\tau_b(X, Y) = S \div \left(\sqrt{\left(\frac{n(n-1)}{2} - T_X\right)}\cdot\sqrt{\left(\frac{n(n-1)}{2} - T_Y\right)}\right)$, where T_X and T_Y denote the number of ties in the rank pairs of X and Y, respectively (in adaptation of the formula given in (Szmidt and Kacprzyk, 2011). Kendall’s τ is non-parametric and is stable even in the presence of far outliers (Long and Cliff, 1997). The coefficient allows us to gauge the strength and direction of the common monotonic relation between two variables. We test for significance on the 5 % level (H_0: $\tau = 0$; H_1:$\tau \neq 0$).

We use multiple linear regression to analyze the change in mobility behavior with regard to the choice of transportation modes. In linear regression, a set of exogenous variables – the predictors – are used to estimate an endogenous variable – the target variable. The resulting model assumes strictly linear relationships of the endogenous variables with each predictor and can be expressed by the equation $y = \beta \cdot X_t + \epsilon_t$, where, for every data point t, y_t is the endogenous variable, ϵ_t is the estimation error of the fitted model, X_t is the design matrix containing the selected predictors, and β is the vector of regression coefficients, indicative of the strength and direction of the respective relations.

The fitted model, which is fitted to the available data, is evaluated using the extent of the remaining error, that is, the aggregated difference between observed values y_t and the estimated values $\hat{y_t}$ of the target variable. The lower these residuals for the model, the better the fit. Accordingly, as measures for model selection, we use the (adjusted) coefficient of determination R^2. Additionally, the Akaike and Bayesian information criterion (AIC and BIC), both likelihood-based measures, are used for model selection. In contrast to the basic R^2, these measures are corrected for the number of variables in the model (i.e., the degrees of freedom) and, thus, are less prone to overestimating model fit as a reaction to potentially too many variables.

Table 1
Relative change of the mode-specific annual averages of monthly trips and distances compared to the pre-pandemic reference period.

	Total	Bicycle	Car	Public transportation	Walk
Trips	−10,79 %	52,58 %	2,64 %	−49,91 %	−7,09 %
Distances	−19,91 %	116,66 %	6,65 %	−43,16 %	7,41 %

Note: Mar 2020 – Aug 2021 (pandemic period) vs Jan 2019 – Dec 2019 (pre-pandemic reference period).

In order to determine and qualify the occurrence of modal shifts during the COVID-19 pandemic in the years 2020 and 2021 according to the data at hand, we fit regression models, using the average weekly number of trips and average weekly distance, respectively, traveled in public transportation as the target variable. The set of predictors is then composed of the average number of trips / average distances traveled using other modes of transportation and the local weather, indicated by the observed daily precipitation, temperature, and snow cover. The estimated models exhibited varying degrees of auto-correlation, which is mitigated by introducing the 1-lag difference of the target variable as a predictor. Furthermore, the weekly average temperature was added to the models as a proxy for the observed weather conditions, as these may alter mode choices.

4. Results

4.1. General mobility change in Berlin

Average trips. With the pandemic hitting Germany in March 2020, the number of average trips drastically decreased over a four-month period, reaching a low point in June (-45 % compared to June 2019). The decrease was a result of reduced social contacts due to partial curfews and the cancellation of commuting trips due to many working from home during and after the installation of a seven-week lockdown (22 March–4 May 2020). Despite trip frequencies having recovered to a pre-pandemic level during summer, the swelling of the second wave in October resulted in a renewed reduction of trips. In the context of Germany installing the second full lockdown as of 16 December 2020, trip frequencies lay again below the pre-pandemic level by the end of the year. As a result of the second lockdown remaining in force for the entire winter period and comparably harsh weather conditions, trip frequencies continuously decreased in early 2021, culminating in a relative low point of average trips remaining 20 % below the respective pre-pandemic level in January 2021. In the following months, trip frequencies relatively exceeded the pre-pandemic level by up to 5 % in spring 2021, before falling significantly over summertime.

Fig. 1 illustrates the longitudinal development of absolute trip frequencies. Summarizing the long-term changes induced by the 20-month pandemic period, average monthly trip frequencies had decreased by about 11 % compared to the pre-pandemic reference period.

Average distances. Starting from a high level of average traveled distances in early 2020 possibly also due to mild weather conditions, the start of the pandemic in March 2020 resulted in a massive reduction of traveled distances over a three-month period, reaching a rock bottom in April in absolute terms and a relative low point in May 2020 (40 % below pre-pandemic level).

In contrast to the average number of trips having been further reduced until June 2020, average traveled distances already started to recover after April 2020, reaching an absolute peak in August 2020 and almost getting back to a pre-pandemic level in relative terms. However, in the following months, trip distances again significantly decreased in the light of rising COVID-19 cases and tightening governmental measures to control the second wave. Notably, despite the installation of a full second lockdown, traveled distances slightly regained in December 2020. Nevertheless, monthly trip distances in the second half of 2020 altogether remained far below the pre-pandemic level. Analogous to the number of average trips, the beginning of 2021 saw a decrease in traveled distances and a regain in spring and summer, culminating in a temporary peak in July 2021. However, while traveled distances plunged over an extended period during the first pandemic wave in 2020, traveled distances during the third pandemic wave in spring 2021 lay almost 50 % above the previous year's level. Except for August, traveled distances per user in spring and summer 2021 were relatively higher than in 2020. In the long term, average monthly travel distances during the 20-month pandemic period had decreased by about 20 % compared to the pre-pandemic reference period (see Table 1).

4.2. Change of mode choices during the pandemic period

Induced by the pandemic, mode choices in 2020 were characterized by major alterations that reached far beyond the typical seasonal oscillations (see Figs. 2 and 3 for a visual reference). After the (pre-pandemic) beginning of 2020 started with unusually high mobile activity across all modes, the pandemic reaching Germany in March 2020 changed the established modal use patterns entirely.

Most significantly, walking and public transportation trips plummeted (see Fig. 5). Walking trips steadily decreased for a four month-period, reaching a rock bottom in June, represented by walking trips having almost halved compared to the previous year. More severely, the number of trips conducted by public transportation fell from a significant level in the beginning of the year to an almost negligible amount in April 2020, representing a relative drop of about 68 % compared to April 2019. As a consequence, distances traveled by public transportation had dropped by around 77 % in April 2020 compared to April 2019. Completing the illustration of this particular sectoral crisis, we note that public transportation accounted for a total share of only 7.3 % within the

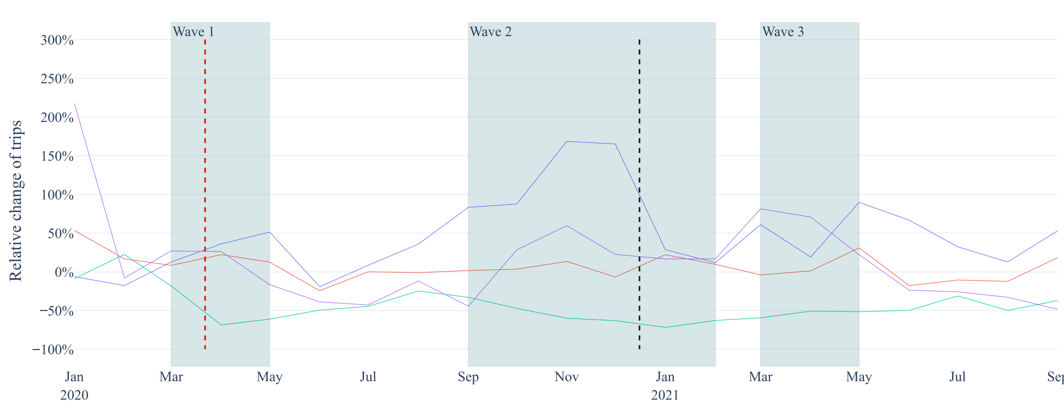


Fig. 2. Relative change of mode-specific trip frequencies (2020–2021 vs 2019).

Fig. 3. Relative change of mode-specific travel distances (2020–2021 vs 2019).

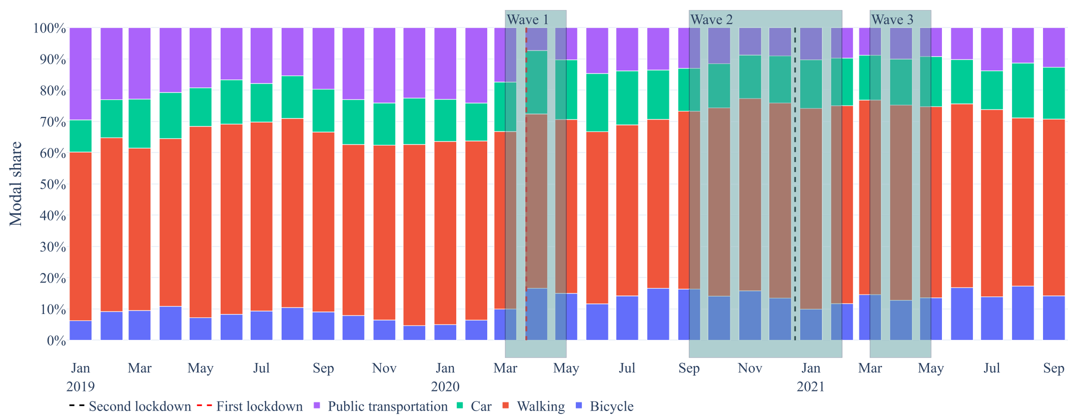


Fig. 4. Modal split (Jan 2019–Sep 2021).

Fig. 5. Absolute change of mode-specific trip frequencies (Jan 2019–Sep 2021).

modal split of April 2020 (see Fig. 4). Despite a slight recovery in summer 2020, the second wave hitting Germany in September 2020 resulted in a renewed drastic plunge of public transportation trips. Thus, public mode choices remained far below the pre-pandemic level over the course of the entire year.

In contrast to the relative unattractiveness of public modes, the number of trips conducted by car and bicycle had increased since the start of the first wave in spring 2020. During the first lockdown period, average monthly trips conducted by bicycle reached a preliminary peak in April and had equaled the number of car trips. In the months which followed, the absolute number of bicycle trips increased at a moderately higher rate than the absolute number of car trips. Car trips in general were the most constant mode in 2020, with comparably little absolute and relative fluctuations. Further illustrating the growing attractiveness of cycling during the first pandemic wave, bicycle trips in May 2020 saw a relative surge of about 51 % since May 2019. Moreover, bicycle-related travel distances had increased by around 78 % in April compared to the previous year's level. After an interim reduction of bicycle trips during summer, the second half of the year saw a manifest increase, which exceeded the amount of car trips for several months in the context of Germany facing the dawn of the second wave starting from September 2020. In relative terms, the amount of bicycle trips exceeded the previous year's level over the course of the entire year, reaching the peak points of a 169 % increase in November 2020 and

Fig. 6. Absolute change of mode-specific travel distances (Jan 2019–Sep 2021).

respective travel distances having increased to 372 % in December 2020.

While walking regained its status as being the most frequently used transportation mode in 2021, all relevant parameters for public transportation indicate the sector to have continuously suffered also in the second year of the pandemic, thus manifesting a long-term negative effect. Despite a slight recovery in summer, the average number of trips conducted by public transportation between January and September even remained below the already low levels of 2020. In contrast to the continuous lack of attractiveness of public transportation, individual modes gained further ground. Whereas car use in the covered period January–September 2021 remained relatively stable, it was used for longer distances than in 2020, the trend of using the bicycle more often and traveling longer distances also clearly continued during the second year of the pandemic.

Summarizing the long-term relative changes of mode-specific parameters (see Table 1), the bicycle experienced the most drastic increases, while public transportation has lost much of its former relevance. Furthermore, the relevance of car travel didn't change across the entire period, while walking has lost little ground.

Illustrating these changes in the modal split (see Fig. 4), walks remained the backbone of everyday mobility during the pandemic, while cycling tended to occupy the lost ground once held by public modes. Further illuminating the relationships between different modes of transportation in Berlin, and how these have changed during the COVID-19 pandemic, we have looked into correlations between the average weekly number of trips and the average weekly distance traveled for each transportation mode.

For the pandemic period from 1 March 2020 until 30 September 2021, transportation modes were behaving more reciprocally than before. Car trips exhibited the least variation in relation to other modes and even in the total number of weekly per user trips. Considering the traveled distances, we can find mostly negative correlations for bicycle distances with most other modes, walking distances exhibit little resonance. Correlations with other modes of transportation and the total distances are weakly negative. Only the correlation with car distances is significant, hinting at a weak inverse relationship. This means that, during the pandemic period, walking distance changes were not aligned with other transportation modes or the total distances traveled. On the contrary, there is evidence that walking had a compensatory effect.

To further investigate these special relations, regression models were fitted[1] and analyzed in an effort to verify the findings from the correlation analysis. We can see that temperature appears to be well suited as a predictor, since both the number of trips (regression coef.: 0.0890) and the distance traveled (regression coef.: 2.8528) increased significantly with every degree Celsius. Experiments using the amount of precipitation or snow, instead, yielded insignificant results. Different from the correlation analysis, we can find that bicycle rides may have replaced public transportation trips. For the distances traveled, we can find a similar effect, which would suggest that almost every kilometer increase in bicycle distance arose from changes in public transportation use.

While neither car trips nor distances appear to have a significant impact on public transportation, walking trips and distances were significantly positively related to public transportation (trips regression coef.: 0.2417; distance regression coef.: 4.9459). This stands in contrast to the correlation results, yielding a significant positive correlation (0.451) for the weekly number of per-user trips, but not for the distances traveled.

4.3. *Intra-pandemic dynamics*

In the following paragraphs, the pandemic period as discussed above is decomposed into three major pandemic waves. The waves define periods of high incidences and high reproductions rates, which were accompanied by a multitude of governmental measures. Within the period covered, we distinguish three pandemic waves: First wave (March–May 2020), Second Wave (September 2020–February 2021), and Third Wave (March 2021–May 2021). For reference, Figs. 5 and 6 depict the timeline with respect to absolute trip frequencies and distances traveled by mode against intervals which represent each of the pandemic waves.

First Wave (March–May 2020). The first pandemic wave comprised a short and rapid swelling phase that was met by the abrupt installation of a full lockdown. Despite the fast-spreading infection and societal inexperience with the situation, notable changes in mobility behavior appeared rather late. The first verifiable reductions of trip frequencies and traveled distances can be traced back to the last week before the lockdown (16–22 March), which can be interpreted as a first adaptive response against the background of COVID-19 cases whose number had grown exponentially for the second week up to that point. Thus, the shift in mobility behaviors can be seen to have already begun shortly before the installation of compulsory governmental measures (social distancing, school closing, travel bans, etc.). More specifically, this shift was mainly realized by a sharp reduction of trips conducted by public transportation, which saw a drastic drop of 27 % in calendar week 12 (16–22 March in 2020) compared to calendar week 11 (9–15 March). Notably, the previous three weeks had shown a very stable situation in which the amount of public transportation trips had slightly increased. This significant reduction of trips conducted by public transportation may provide the first empirical evidence of a behavioral response in the form of avoiding public transportation means, which were perceived to contain a higher risk of infection.

[1] p-values for F: ≪ 0.05 with Adj. R^2 of 0.64 and 0.82. This means that the regression models can explain about 64 % of the variation within the number of weekly per-user trips, and even 82 % of distances variation.

However, the lockdown – put into force as of 22 March 2020 – resulted in more drastic reductions than individuals' voluntary behavioral responses to the surging incidence rates before the first lockdown. Hence, the drastic decrease in trip frequencies and traveled distances in the first week under a full lockdown (22–28 March) indicates that during the first pandemic wave, strict governmental measures effectively restricted personal mobility. In this particular week, trip frequencies dropped by 23 % and traveled distances by 51 % compared to the previous week. This drop affected all modes except bicycle trips, which moderately increased by 11 % compared to the previous week. During the first week of the lockdown, the strongest decrease occurred in the number of public transportation trips (57 %) and walks (23 %). Accordingly, traveled distances by public transportation and cars plummeted by 73 % and 33 %, respectively. Contrary to these developments, the average weekly distance for bicycle trips strongly increased by 54 % compared to the week before the lockdown. Aggregated on a monthly level, traveled bicycle distances showed a relative increase of about 78 % in April 2020 compared to the previous year's level. This development is noteworthy against the background of a generally strongly reduced activity radius, illustrated by the fact that average trip distances across all modes had fallen from 7.13 km in (pre-pandemic) January 2020 to 4.92 km in April 2020.

In the following months, the development of reduced mobile activity showed a sense of latency as trip frequencies continued to drop until June 2020. Interestingly, this occurred despite the number of positive COVID19 cases having stabilized in the meantime and the first lockdown ending on 4 May. However, this latency was compensated by an increase in traveled distances in the same month, thus indicating a tentative trend of mobilitybehavioral recovery. However, significant recovery towards a pre-pandemic level did not happen before mid-June 2020, illustrating the collective shock induced by the first wave that led to drastically curbing established mobile practices.

Trip frequencies for modes (see Fig. A.2a) show a mostly positive correlation with one another, and with the total average number of weekly trips. During the first wave the number of walking trips decreased monotonically with the total number of trips, whereas public transportation trips experienced a reduction which was less pronounced than for walking trips. Thus, trips performed by car or by bicycle showed weak reactions to the overall reduction in weekly trips. Instead, we can find evidence that users swapped trips between the two modes during the first wave.

Examining the correlation between traveled distances (see Fig. A.2b) provides insights into possible exchange relations between the modes. It shows that, while the number of bicycle trips did not change in significant correlation with the total number of trips, the overall bicycle distances increased significantly with a reduction in every other transportation mode, except for walking. Furthermore, we can observe a relatively strong correlation for public transportation with the overall distances traveled, indicating a more pronounced reaction to the overall decreasing mobility.

Second Wave (September 2020–February 2021). In contrast to the first wave, trip frequencies in the second wave did not reduce before the installation of strict governmental measures. Average trip frequencies still continued to increase slightly in September and October 2020. However, most notably, this increase did not apply to public transportation trips, which had already started to decline by early October. Hence, in the context of a re-accelerating pandemic, a share of people started again to change their mobility practices by avoiding trips in trains and buses. Compared to the start of the second wave in September 2020, trips conducted by public transportation had dropped by about 9 % in the following month. Thus, both waves showed the similarity of individuals creating first mobility-behavioral responses in the form of avoiding public transportation trips even before the installation of strict governmental measures. However, as the reduction of trip frequencies in the first wave – in contrast to the second – affected all modes, the exclusive reduction of public transportation trips during the swelling of the second wave indicates that individuals tried to remain as mobile as possible by shifting to other modes. This perpetuation was realized more distinctly than during the swelling of the first wave by a relative increase in bicycle use.

Moreover, the swelling phase shows a likeness with the first wave concerning the decrease in traveled distances. Despite trip frequencies still slightly increasing in September and October, traveled distances dropped by around 14 % from September to October. Hence, the swelling phase of the second wave can be characterized by trip frequencies remaining high while distances were shortened. Like during the first wave, this reduction can be explained by a reduction of traveled distances in public transportation.

Regarding the effect of governmental measures, the comparison of the two waves shows some similarities between them. After the declaration of a "lockdown light" in early November, trip frequencies and traveled distances reduced significantly. This reduction mostly affected the number of public transportation trips, which significantly dropped by about 30 % compared to October and by about 36 % compared to September. In addition, travel distances were reduced by about 40 % and about 57 % in October and September, respectively. Moreover, within the first week of the full lockdown (16 December), trip frequencies for all modes decreased entirely, illustrating a likeness to the first wave regarding the effectiveness of lockdowns for instantly reducing a share of individuals' mobile activities. However, in contrast to the first wave, the total amount of traveled distances was not significantly reduced within the first week of the lockdown, in fact, it increased slightly in the following weeks. This was possibly related to higher travel demand around Christmas. Thus, the two waves show a slight difference regarding traveled distances not reducing linearly in the second wave, but regaining temporarily in December 2020 before declining again in early 2021.

At the peak of the second wave in December 2020, there was a marginal increase in walks and car trips (about 9 %) compared to the previous month. At the same time, the decrease in public transportation trips stabilized on its low level. Moreover, the gains in bicycle trips that were established by the end of the summer persisted, despite the seasonal inconveniences that traditionally make cycling less attractive around the end of the year. After the huge relative gains illustrated in Chapter 4.2, bicycle trip frequencies temporarily narrowed to an almost pre-pandemic level in January and February 2021 (probably also caused by harsh winter conditions). However, respective travel distances clearly remained relatively higher for the rest of the winter compared to pre-pandemic times.

Against the background of a repeated lockdown extension due to continuously high infection rates, trip frequencies and travel distances continued to decrease, reaching a minimum in February 2021. While this decrease affected all modes, it especially applied to public modes. A light recovery phase was detectable in March, which was however occurring parallel to the swelling of the third pandemic wave.

Again, analysis of the association between means of transportation shows that the first wave appears to have a lasting impact on user behavior. During the second wave, policy changed from a phase of relatively moderate measures towards a second phase of returning to a more rigorous lockdown. The results of the correlation analysis, conducted for both phases, show their differences with respect to changes in mode choice behavior (see Fig. A.2c and A.2d for phase 1, and A.2e and A.2f for phase 2).

During the "lockdown light" (phase 1), trips exhibited similar correlation patterns as during the first wave, now showing significant positive correlations for bicycle and car trips with total and public transportation trips. However, bicycle distances are now positively correlated with other modes except walks. Probably having hit a saturating level, with overall mobility not fully recuperated to the pre-pandemic level, distances traveled by bicycle are now decreasing in the total distance traveled, showing the same behavior as car trips and public transportation. It appears as though in phase 1 of the second wave, users were increasing the average walking range, while reducing the average distances traveled in other modes.

During phase 2, after the tightened lockdown came into force, only a few significant correlations can be identified. With regard to trips, only the number of public transportation trips and walks appear to be in a significant (positive) association with the overall mobility and with each other, respectively. The other modes have insignificant, albeit non-marginal positive correlations. With respect to the distances traveled, most remarkably, the observed increase in walking distances persists against the reduced overall traveling distance. Furthermore, traveled distances using public transportation now exhibit weaker correlation with the overall distance traveled than car distances. This finding may be indicative of the public transportation usage nearing a bare minimum.

Third Wave (March 2021–May 2021). In contrast to the swelling phase of the second wave and in analogy with the first wave, the third saw a stronger reduction of average trips, while traveled distances remained stable. The amount of trips decreased by about 12 % from March to April, which marked the third wave's most critical phase, while average distances in the respective period remained unchanged. Interestingly, the overall reduction of trips did not affect public transportation for the first time in the pandemic, which – though on a very low level – remained stable during the entire wave period. In contrast, frequencies of bicycle, walking, and car trips decreased during April 2021. Regarding traveled distances in April 2021, bicycle and walking trips decreased, while car and public transportation distances remained stable. Despite public transportation having stopped losing ground in the third wave, traveled distances in April 2021 still lay 35 % and trip frequencies about 51 % below the pre-pandemic level of April 2019. This stabilization on a low level was probably due to a particular share of the population that was obliged to use public transportation regardless of the pandemic situation (health service employees, blue-collar workers, etc.). On the other hand, the stabilization may be explained by a new degree of riders' confidence thanks to the start of the vaccination campaign. Moreover, the trip- and distance-related reductions of individual transportation means may be also explained by April 2021 being the coldest April in 40 years, thus impeding the start of seasonal push effects, especially for cycling (DWD, 2021).

In the context of decreasing incidence rates and mild weather conditions in May 2021, trip frequencies and traveled distances significantly regained. The relaxation from the interim reduction of mobile activities in April was detectable across all modes, and was in particular supported by a relative increase in bicycle and car trips. Hence, in comparison to the relaxation phase of the first wave that took place in a similar seasonal context, the recovery of mobile activities during the third wave was quicker and included both overall trip frequencies and traveled distances.

In contrast to the other waves, we can find only a few significant correlation coefficients (see Fig. A.2g and A.2 h). Regarding weekly trips, only car use and walking trips have significant positive correlation with the total average number of trips, meaning that both frequencies sank in conjunction with the overall mobility. Similarly, negligible correlation can be observed for bicycle and walking distances. Public transportation does not show significant correlation with the total per-user number of trips or the traveled distances. This might suggest that mode choices for the crisis state were mostly settled at that point, and major alterations in the overall mobility were already mostly realized by cars and walking.

5. Discussion

5.1. Assessing the pandemic's long-term changes

Our findings suggest the pandemic to have substantially changed urban mobility behaviors. This change not only occurred temporarily during periods of high infection rates, but also in the long term. While the first three pandemic waves showed periodically drastic (though gradually softening) reductions of mobile activity, the long-term changes manifest in the form of a continual absolute and relative decrease in individuals' trip frequencies and traveled distances. With traveled distances between March 2020 and September 2021 having been relatively reduced by about 20 % compared to the pre-pandemic reference period, the transportation-related fulfillment of everyday requirements appears to have taken place in unprecedented vicinity of peoples' residences. Moreover, individuals did not only tend to travel shorter distances, but the long-term relative reduction of about 11 % in trip frequencies hints that individuals also tended to travel less often, compared to the pre-pandemic reference period.

These central findings provide empirical evidence for COVID-19 having generated fundamental changes to traditional drivers of mobility demand. Besides the temporary unavailability of educational, childcare, and cultural facilities which contributed to decreasing mobility demands, various studies addressed work-related transformations to have particularly accounted for reduced mobility demand. The share of workers in Germany that mostly or always work from home increased from 4 % before the pandemic to an interim peak of 27 % during the first lockdown (Ahlers et al., 2021). Researchers examining trips in the Netherlands, found the total amount of work hours during the first lockdown to have been spent in equal shares at the workplace and at home (Zimpelmann, 2021). Job losses, particularly experienced among self-employed workers in the service sector (Block et al., 2021), and employees in short-time work, also contributed to reduced physical mobility demands. Despite these work-related transformations underlying seasonal and incidence rate growth-related fluctuations, they can explain our finding of a drastic reduction of traveled distances due to the reduction or cancellation of commuting trips, especially those conducted by public transportation (de Haas et al., 2020).

Concerning mode choices, our results show that public transportation continued to lose ground not only in the first but also in the second pandemic year, illustrated by trip frequencies experiencing a relative long-term reduction of almost 50 %, and traveled distances decreasing by about 43 % compared to the pre-pandemic reference period. This finding adds to a growing body of studies that found public transportation in urban areas to be the most affected mode (Abdullah et al., 2020; Bucsky, 2020; Barbieri et al., 2021; Aloi et al., 2020; Teixeira and Lopes, 2020). However, while most studies assigned these findings to the first lockdown in early 2020, our results demonstrate that the crisis of public transportation — despite periods of recovery during summer 2020 and 2021 — also continued in the pandemic's subsequent periods. Hence, based on our findings for Berlin, we can confirm the global observation that public transportation must be declared the modal loser of the pandemic. Further qualifying this observation, our longitudinal analysis indicates a structural rather than just a temporary behavioral change in using public modes. This finding aligns to other studies that suggest the sector will suffer from long-term structural problems, for example, by showing that workers, especially those with higher education or who were former car commuters (Rubin et al., 2021), have formulated the clear expectation to also work from home in the future (de Haas et al., 2020; ADAC, 2021). Apart from work-related transformations, empirical studies have revealed a general long-term intention to reduce public transportation use (Przybylowski et al., 2021; Thomas et al., 2021; Harrington and Hadjiconstantinou, 2022). In order to counteract public transportation entering a further downward spiral and also to compensate for the sector's decreasing CO2-efficiency in light of decreasing ridership (Umweltbundesamt, 2022), transportation policy might have to consider the use of drastic measures to attract the use of public transportation, as recently experienced in the case of the German 9€ travel pass, which was introduced for three months and allowed individuals to use public modes during one month for a single reduced fare. The success of this particular initiative led to a vibrant discussion about additional and long-term measures that would attract public transportation in the future.

In addition to highlighting the regressive usage of public means of transportation, our study revealed the pandemic to have increased the relevance of individual modes. Whilst walking quantitatively remained the primary mode choice across the entire period, our analysis nevertheless suggests the bicycle to be the central modal beneficiary of the pandemic. The surge of bicycle-related trips and traveled distances started in the first wave and accelerated during the second. Though this finding is in line with other studies that found bicycle use to have increased during the first wave (de Haas et al., 2020; Abdullah et al., 2020; Molloy et al., 2021), our longitudinally-derived findings indicate the bicycle to have received its actual relevance as a function of the pandemic's longevity. Unveiled by correlation analysis, the substantial surge in bicycle use and traveled distances during the second wave may be explained by people increasingly using the bicycle as a substitution for public transportation. Moreover, studies analyzing, for example, the change of bicycle-sharing use during the pandemic indicate cycling to have become increasingly used for recreational purposes (Consumer Data Research Center, 2022). Irrespective of the particular travel purpose, the installation of pop-up bicycle lanes in Berlin may have created a pull effect for cycling and a stimulation for extended use beyond traditional seasonality. In this vein, our findings may also provide empirical grounds for the bicycle-friendly redesigning of streetscapes, having met (or catalyzed) growing demand for cycling (Kraus and Koch, 2021). Given the effectiveness of such infrastructural measures, the systematic and permanent redesign of streetscapes for cycling and walking can be considered a key policy and planning implication, which may contribute to making cities more resilient to future pandemics in the sense of keeping the population mobile, while at the same time reducing dependencies on motorized traffic.

Despite growing preference for individual modes, the car cannot be considered a long-term beneficiary of the pandemic. In our data, we found evidence that individuals swapped trips between car and bicycle during the first wave. To a greater extent, they appear to have swapped traveling distances from cars to bicycles. However, considering the entire pandemic phase, car use has only changed moderately, yet reciprocally with the overall mobility and activity levels. Hence, the conclusion can be drawn that, while cars act as a kind of backbone for mid-ranged transportation (e.g., for commuters), they were not used as a compensatory means. These findings contrast various studies that noticed an increased car use during the first lockdown period (Abdullah et al., 2020; Bucsky, 2020; Beck and Hensher, 2020; Knie et al., 2021).

Our findings on this may be explained by Berlin residents having faced economic, structural, and cultural limitations for instant accessibility to car travel. As a city of a comparably low socio-economic status, instant car ownership may not have been affordable for many. Moreover, the registration of a new car was structurally hampered by licensing offices that had strongly reduced their work capacities. In summer 2020, customers had to wait for more than two months to receive a license, thus making it unlikely to swiftly acquire a new car as a compensatory mode. Finally, Berlin possesses a historically-grown public transportation and active mobility culture. Walking, cycling, and public transportation together accumulated a modal share of 74 % right before the pandemic (Gericke et al., 2020), making Berlin the least motorized city in Germany with 336 registered passenger cars per 1,000 inhabitants, compared to a domestic average of 580 (KBA, 2021). Thus, behavioral shifts towards other modes, for example, the bicycle, may also have been culturally-informed decisions. More rationally, shifts to bicycle travel may have been considered comparably simple, cheap, and effective for the purpose of reaching a portion of destinations that were formerly reached by public transportation.

5.2. Differentiating intra-pandemic behavioral responses

Our analysis of the intra-pandemic dynamics suggests that each pandemic wave created unique behavioral dynamics. While the first pandemic wave was characterized by a massive general reduction of individuals' mobile activities and comparably moderate compensatory modal shifts, the second and third wave showed less mobile reduction but stronger compensatory actions in switching to other modes. Generally, long-term changes of mobility behaviors appear to have been catalyzed by periods of high infection rates rather than periods of a relatively stable public health situation.

Individuals' switching to other modes (especially the bicycle) can be interpreted as a learning effect of how to adapt to a persisting crisis and as an ambition to regain some sort of situational control. However, as our data does not provide socio-demographic determinants, there is a need to better understand which specific groups were able to gain from such a learning effect and which were not. In addition to a possible learning effect, our finding of a gradual decrease in mobility-behavioral reactions over the course of the pandemic may also be interpreted as signs of overall pandemic "fatigue" (Zhao et al., 2006) or "social distancing inertia" (Ghader et al., 2004). Indeed, the second wave did not show an equal reduction of mobile activity compared to the first wave despite growing incidence rates, numerous fatalities, and lacking availability of a vaccine. This relationship was also confirmed by other longitudinal studies (Kim and Kwan, 2020), thus suggesting that some people either felt tired of following regulations of social distancing and staying at home, or obtained an altered risk perception. However, rather than being a real behavioral phenomenon, the fatigue argument has also been criticized as being a tool for designing policies (Harvey, 2020). In this sense, decreasing adherence to regulations is believed to be more likely to result from existential fears (e.g., job loss), confusing rules, or governmental miscommunication (Michie et al., 2020). Moreover, rather than by element of "fatigue", the comparably more drastic reductions of mobile activities during the first pandemic wave may also be explained by the general atmosphere of a "shock", which included the perception of high uncertainties due to a lack of information about the disease and its contagiousness.

Regarding the waves' similarities, the first and the second wave showed a clear convergence in terms of a tendency to voluntarily avoid public transportation even before the installation of mandatory measures (Ghader et al., 2004). However, changes remained small-scaled, suggesting a hesitancy for preemptive behavioral change during the swellings of the first and second waves. This finding hints to individuals' difficulty (or unwillingness) to change established routines and habits, which can translate into strong behavioral stability over time (Scheiner, 2018). Whereas the concept of habits has been consulted to explain the difficulty of acquiring more sustainable travel behaviors (Fujii and Gärling, 2003; Busch-Geertsema et al., 2015), our findings indicate the stability of travel-related habits to also explain the actual need of behavioral change in the pandemic context.

On the other hand, our findings of drastic changes of trip frequencies and traveled distances after the installation of a full lockdown has shown the effectiveness of strict governmental measures in reducing mobile activity. This suggested effectiveness of governmental measures aligns to various studies that found mandated measures to be more effective in decreasing mobility and incidence rates compared to voluntary measures (Kim and Kwan, 2020; Woskie et al., 2020; Müller et al., 2020).

5.3. Limitations

Our work is limited by several factors. First, our data is not demographically representative for the Berlin population, as for privacy reasons we are lacking information about the sample's demographic characteristics. However, comparing our results to studies with bigger and representative samples derived from the same geographical context (Bohnensteffen et al., 2021) showed various overlaps, which leads us to assume representativity for our sample. Nevertheless, knowledge about (socio-)demographic characteristics (age, gender, education) would have allowed us to ascertain a more differentiated picture of mobility-behavioral responses to the pandemic. Second, for the correlation analysis, it is worth mentioning that Kendall's correlation coefficient measures monotonic instead of linear relations between variables, which somewhat limits the strength of the conclusions that can be drawn. Third, it is worth mentioning that the modes in the dataset result from estimation by means of an algorithm. In the study by a Swiss research team, the algorithm was able to detect major transportation modes with very high accuracy (see Molloy et al., 2022, Table 7), independent of the operating system. Trips traveled by bus were detected with relatively low accuracy of about 66 %. One important reason is that either car trips were wrongfully labeled as bus trips or bus trips were mistaken for car trips (see Molloy et al., 2022, Table 8). However, for the setup in this study, these misclassifications are of little consequence. Fourth, the year 2019 was normal in the sense that a COVID-19 pandemic was not in sight. However, it is not guaranteed that mobility in 2019 was not influenced by any anomalous effects. In order to better understand how human mobility behavior changed during the pandemic, a longer pre-pandemic dataset would be beneficial. Unfortunately, the authors were not able to receive additional data since data collection by the two respective apps started not until 2019.

6. Conclusions

COVID-19 can be considered a game changer for individual travel behaviors. Our longitudinal investigation of behavioral transformations derived from a sample of Berlin residents revealed that the pandemic induced a continual decrease in individuals' trip frequencies and traveled distances. At the same time, individuals' mode choices significantly shifted towards using individual modes for the price of drastically decreased use of public modes. Despite these changes having particularly occurred during periods of high infection rates and their respective lockdowns, the findings of our study covering a 20-month pandemic period provide a first glance of the pandemic as having created long-term effects that may constitute a "new normal".

This "new normal" may be described as a mobility landscape in which (i) people tend to travel less often and for shorter distances, and (ii) have developed a habitual preference for individualized transportation. What's more, this "new normal" may (iii) be described as a landscape in which public transportation has lost relevance, thus opening the political challenge of the sector's increasing financial needs for achieving long-term policy goals, for example, inclusive and sustainable transportation. In light of these challenges, transportation policy should take measures that not only aim to correct today's problematic situations by readjusting measures, but should also help to prevent the repeated immobilization of parts of the society in the case of future pandemics through a profound redesign of streetscapes that facilitate bicycle and walking traffic. Considering COVID-19 an external shock to the transportation system, it can generally be speculated whether shock-induced changes of the mobility behavior can be extenuated exclusively by measures of equal disruptive potential. In fact, it might well be that even less extreme measures can contribute to a speedy recovery of the transportation system as well.

Regardless of the definite peculiarities we experienced in studying pandemic-induced changes for the case of Berlin, we assume a transferability of our central findings for cities with similar framework conditions. These consist of possessing a strong role of public transportation, a (pre-pandemic) bicycle boom, and a strong political backing for the environmental alliance, as well as for a comparable stringency of governmental measures to control the pandemic. However, in order to further assess the pandemic's long-term effects, there is a need for additional research efforts. Given the pandemic has lasted for more than two years now and having created a complex temporality, we argue for the need to differentiate and contextualize COVID-19-induced mobility phenomena. Therefore, we particularly suggest conducting additional longitudinal studies to empirically test and compare the findings made here. Future research paths could also comprise a combination of longitudinal studies with socio-demographic insights, as well as enriching quantitative results with qualitative findings derived from interviews or focus group discussions in order to illuminate individuals' motives, intentions, and perceptions in changing mobility behaviors. On the optimistic assumption that the near future will bring an escape from the pandemic state of emergency, future mobility-behavioral analyses should aim to capture both the transition phase and the "new normal" and determine whether the findings from this paper hold up to reality.

CRediT authorship contribution statement

Robin Kellermann: Conceptualization, Project administration, Supervision, Writing – original draft. **Daniel Sivizaca Conde:** Data curation, Formal analysis, Methodology, Visualization, Writing – review & editing. **David Rößler:** Formal analysis, Methodology, Visualization, Validation, Writing – review & editing. **Natalia Kliewer:** Validation, Writing – review & editing. **Hans-Liudger Dienel:** Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The authors report funding under the Excellence Strategy of the Federal Government and the Länder by the Berlin University Alliance (project reference: 511_Covid-19). They also acknowledge support by the German Research Foundation and the Open Access Publication Fund of TU Berlin.

Data availability

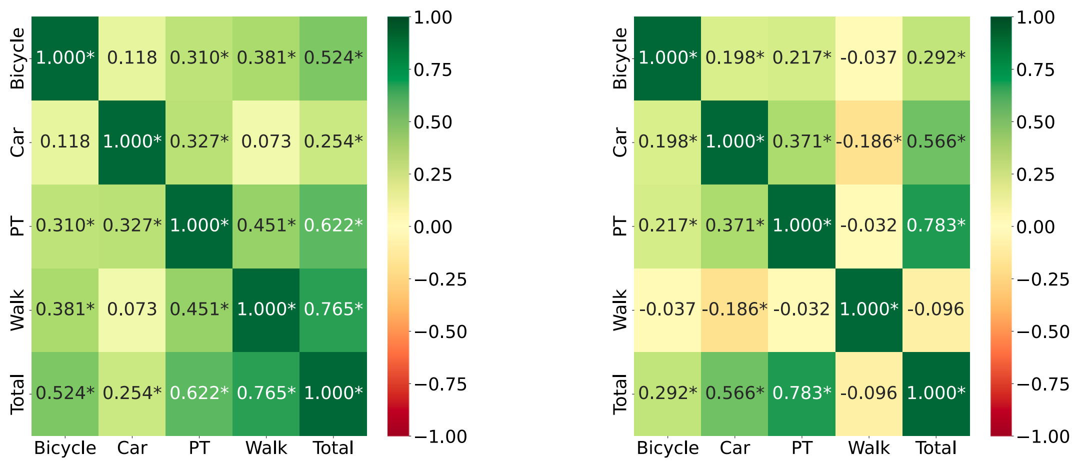
Data will be made available on request.

Appendix A

A.1. Modal shifts before and during the pandemic

Model choice correlation

Model choice regression



(a) Number of weekly trips per user **(b)** Weekly traveled distance per user

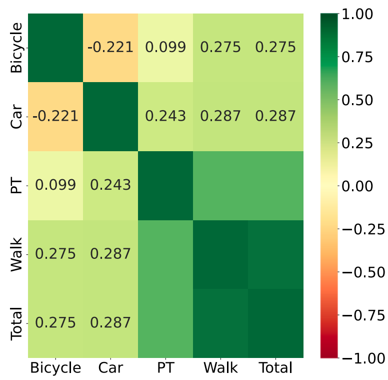
Fig. A1. Correlation matrices (Kendall's τ) for transportation mode choices from 2020-03-01 until 2021-09-30.

Table A1
Summary of linear regression models for average public transportation trips (PT) respective travel distances.

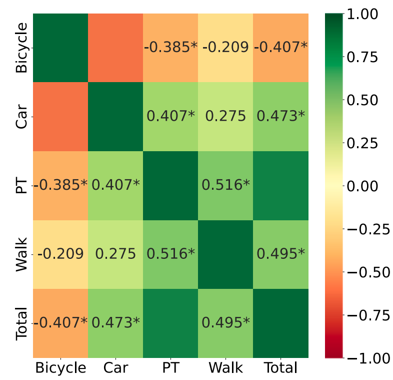
	Model 1	Model 2
Dependent variable	PT Trips	PT Distances
Intercept	−0.5925	−53.5957*
Avg. Bicycle	−0.3329***	−0.9136
Avg. Walk	0.2417***	4.9459**
Avg. Car	−0.1925	0.2178
Avg. Temperature	0.0890***	2.8528***
1-lag PT	0.2719***	0.3999***
Model evaluation		
AIC	50.58	533.3
BIC	63.15	545.8
Durbin-Watson	1.593	2.191
R-squared	0.835	0.670
Adj. R-squared	0.820	0.639
Log-Likelihood	−19.290	−260.64

Note: Statistical significance is denoted by * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

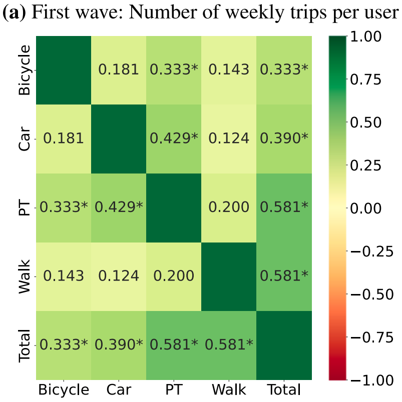
A.2. Correlation analysis of mode usage during pandemic waves



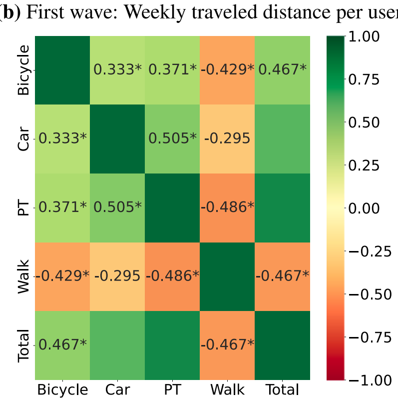
(a) First wave: Number of weekly trips per user



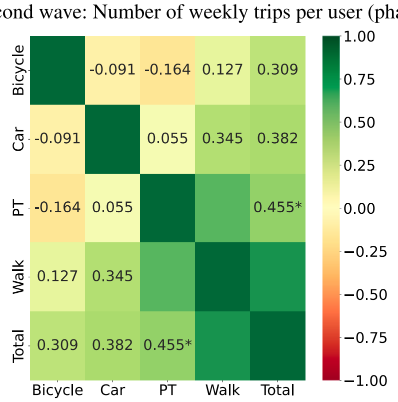
(b) First wave: Weekly traveled distance per user



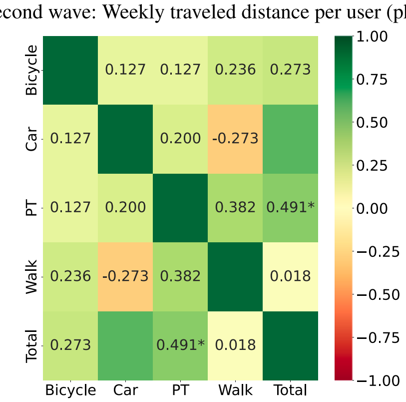
(c) Second wave: Number of weekly trips per user (phase 1)



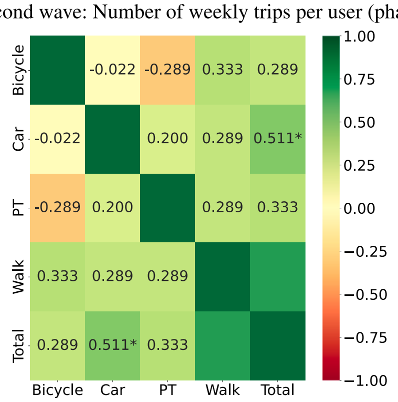
(d) Second wave: Weekly traveled distance per user (phase 1)



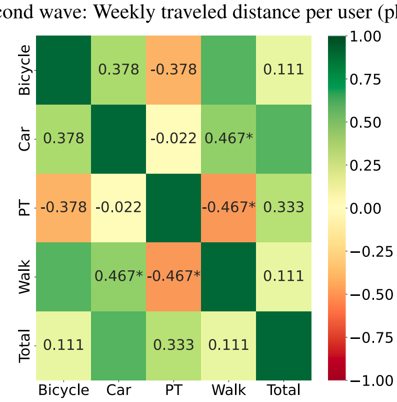
(e) Second wave: Number of weekly trips per user (phase 2)



(f) Second wave: Weekly traveled distance per user (phase 2)



(g) Third wave: Number of weekly trips per user



(h) Third wave: Weekly traveled distance per user

Fig. A2. Correlation matrices (Kendall's τ) for transportation mode choices during the first, second, and third wave.

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