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Human mobility reshaped? Deciphering the impacts of the Covid-19 pandemic on activity patterns, spatial habits, and schedule habits

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Abstract

Despite the historically documented regularity in human mobility patterns, the relaxation of spatial and temporal constraints, brought by the widespread adoption of telecommuting and e-commerce during the COVID-19 pandemic, as well as a growing desire for flexible work arrangements in a post-pandemic work, indicates a potential reshaping of these patterns. In this paper, we investigate the multifaceted impacts of relaxed spatio-temporal constraints on human mobility, using well-established metrics from the travel behavior literature. Further, we introduce a novel metric for schedule regularity, accounting for specific day-of-week characteristics that previous approaches overlooked. Building on the large body of literature on the impacts of COVID-19 on human mobility, we make use of passively tracked Point of Interest (POI) data for approximately 21,700 smartphone users in the US, and analyze data between January 2020 and September 2022 to answer two key questions: (1) has the COVID-19 pandemic and its associated relaxation of spatio-temporal activity patterns reshaped the different aspects of human mobility, and (2) have we achieved a state of stable post-pandemic "new normal"? We hypothesize that the relaxation of the spatiotemporal constraints around key activities will result in people exhibiting less regular schedules. Findings reveal a complex landscape: while some mobility indicators have reverted to pre-pandemic norms, such as trip frequency and travel distance, others, notably at-home dwell-time, persist at altered levels, suggesting a recalibration rather than a return to past behaviors. Most notably, our analysis reveals a paradox: despite the documented large-scale shift towards flexible work arrangements, schedule habits have strengthened rather than relaxed, defying our initial hypotheses and highlighting a desire for regularity. The study's results contribute to a deeper understanding of the post-pandemic "new normal", offering key insights on how multiple facets of travel behavior were reshaped, if at all, by the COVID-19 pandemic, and will help inform transportation planning in a post-pandemic world.

Keywords: COVID-19; Intrapersonal variability; Travel behavior; Big data

1 Introduction

Human mobility has been repeatedly shown to be regular and predictable [1–4]. Such regularity is the result of both internal and external constraints. These include circadian rhythms [5, 6], the need to eat, spatio-temporal commuting requirements [7], psychological traits [8], social responsibilities [9], and socio-economic characteristics [9, 10]. For example, it is easy to imagine how a parent with childcare duties and a fixed work location is constrained to follow a regular schedule with activities that are, for the most part, well-planned ahead of time and regular. Similarly, it is also easy to imagine how a young urban remote worker can flexibly adjust their activities to meet their own needs; not being limited by a fixed work location, this worker can choose to work from different locations, adjust their schedule to run errands during regular business hours when work demands are not intense, and follow working routines that might be synchronous with colleagues from different time zones. Temporal mobility regularity has been shown to lead to increased social contact rates [11–13] and play a critical role in disease spreading processes [14].

In the wake of the COVID-19 pandemic, human behavior underwent significant shifts. Governments, especially during the pandemic's early stages, leaned heavily on non-pharmaceutical interventions (NPI) to curb the virus's spread. These interventions had significant impacts on human behavior, reducing mobility levels, changing lifestyles, and causing ripple effects on physical and mental well-being. A standout change during this period was the large scale adoption of telecommuting by employers and the increase in e-commerce adoption by consumers. The persistent preference for and adoption of hybrid working models and e-commerce by employees and consumers, even after the easing of pandemic restrictions, hint at lasting behavioral shifts [15–17]. Fundamentally, this evolution reflects a relaxation of spatio-temporal constraints around several activities. In a hybrid work paradigm, employees enjoy more autonomy to choose their preferred work environment, be it their home, the office, or some alternative location like cafes, libraries, or coworking spaces [18]. Further, they enjoy more flexibility in their schedules, including when to work and on what days to commute.

The impacts of the COVID-19 pandemic on human mobility have garnered significant attention from transportation researchers. Researchers addressed the impacts of the pandemic on numerous aspects of travel behavior, such as trip-making [19–21], mode use [20, 22–24], trip purpose [19, 20, 23, 25], distance traveled [26, 27], public transit and active transportation [28–32], commuting behavior [30, 33, 34], e-commerce [15, 35], and time-use [36–39], among others.

However, these works have several limitations. First, majority of the research has been myopic to the broader impacts of the COVID-19 pandemic on human mobility, often focusing on singular aspects of travel behavior. Second, this body of work has predominantly addressed the short-term impacts of the pandemic on travel behavior, with little attention given to potential long-term impacts, indicating our lack of collective understanding of what the post-pandemic landscape is shaping up to be. Most critically, our current understanding of the impacts the COVID-19 pandemic and its associated relaxation of spatio-temporal constraints on schedule habits remains missing. Improving this understanding will help inform transportation planning in a post-pandemic world.

In this article, we use passive mobility tracking dataset from a panel of approximately 21,700 U.S. smartphone users, spanning January 2020 (2 months before the onset of the pandemic) to September 2022 (14 months after widespread vaccine availability in the U.S.) to attempt to address these limitations. First, we propose a framework to explore the impacts of the COVID-19 pandemic and its associated relaxation of spatio-temporal activ-

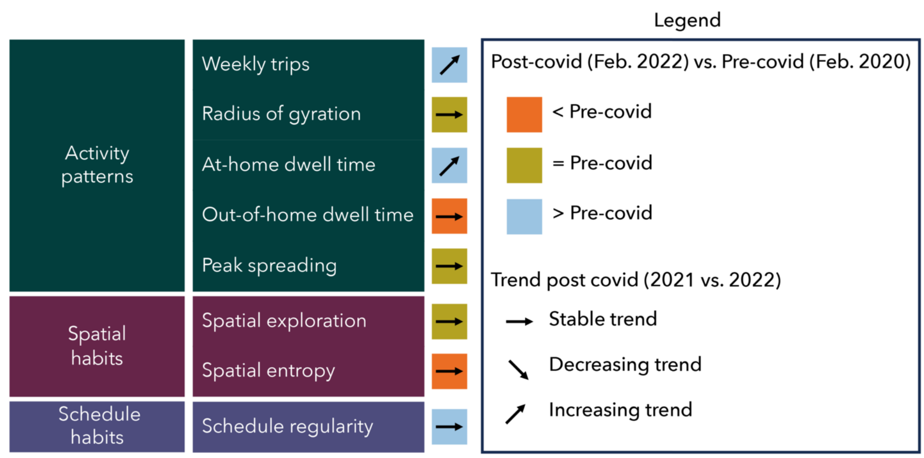

Figure 1 Summary of study findings

ity constraints on multiple dimensions of mobility behavior. We choose well-established mobility metrics from the literature characterizing human activity patterns, namely frequency of travel, radius of gyration, dwell-time, trip timing, spatial exploration, and spatial diversity (as measured by entropy). Second, within this framework, we propose a new metric to measure individual schedule regularity over time, contributing to the literature on intrapersonal travel behavior variability. Finally, we build on the vast COVID-19 travel behavior literature by investigating the long term impacts of the pandemic on travel behavior, providing more clarity on what a "new normal" is shaping up to be. We hypothesize that with the relaxation of spatio-temporal activity constraints during the COVID-19 pandemic, people will exhibit less schedule regularity post-pandemic compared to pre-pandemic.

Figure 1 provides a comprehensive review of our key findings. Our findings present a mixed picture; while several mobility indicators have recovered to their pre-pandemic levels (trip frequency, radius of gyration, peak period demand), others have not (i.e. at home dwell-time). We further find that while people's explorative behavior recovered to their pre-pandemic levels, they exhibit on average lower diversity (as measured by entropy) in their time distribution across space compared to pre-pandemic. Finally, we find that despite the loosening of spatio-temporal activity constraints during the pandemic, schedule habits remain stronger than pre-pandemic, presenting a counterintuitive picture to our initial hypothesis.

The rest of the manuscript is organized as follows; in Sect. 2, we summarize our data, its pre-processing, as well as the analysis framework and approach; in Sect. 3 we present our findings; we conclude with summarizing the study and discussing the possible broader impacts of our findings in Sect. 4.

2 Data and methods

2.1 Data

We leverage passively collected tracking data from a panel of U.S. smartphone users who have consented to give access to their location data. The data was provided by SimilarWeb for research purposes and spans between January 2020 and September 2022, effectively capturing critical long-term behavioral impacts of the COVID-19 pandemic.

These data are not continuously tracked GPS traces, but rather inferred individual check-ins at Points of Interest (POI). SimilarWeb uses proprietary technology from a third-party provider to infer the location category from each of the POIs visited. Further, to preserve the individuals' privacy, SimilarWeb obfuscates the individuals' inferred home and work locations by randomly placing it within a 1000 meters radius from its detected location. For each individual check-in at a POI, the dataset includes information about the panelist's arrival and departure times, the category of the location visited, the distance and time traveled to get to said location, the distance of the POI from the individual's identified home and work locations, as well as its zip code, city, and Metropolitan Statistical Area (MSA) name.

In addition to the POI check-in records, the dataset contains self-reported information about individuals' gender, age, race/ethnicity, household size, household income, educational level, and employment status.

One key advantage of our data is our ability to capture a continuous trajectory of individuals, instead of sparse records depending on the call activity under call detail records data (CDR) or location-based service use for location based service (LBS) data [40, 41]. However, one main limitation of our data is the lack of information about travel modes used for each inferred trip, preventing us from understanding the modal impacts of the COVID-19 pandemic.

To ensure accuracy of our analyses, we undertake rigorous pre-processing to clean our data from any inconsistencies or noise. First, we aggregate each of the POIs visited by each individual into geographical locations based solely on their spatial proximity. This is particularly useful considering that detected spatial coordinates of visited locations can often be noisy [42]. We use the DBSCAN algorithm [43] to cluster the check-ins for each individual using a maximal distance $\boldsymbol{\varepsilon}$. We use a maximum distance $\boldsymbol{\varepsilon}$ = 50 meters and **min_samples** = **1**, to produce places of the approximate size of a building, consistent with previous literature [4, 42, 44]. The result of this pre-processing clustering is an assignment of cluster label to each inferred POI check-in, where the label refers to a geographical place of the POI check-in record.

Second, to maintain high quality observations, we select only individuals observed for a long period of time with small change in tracking coverage over time, consistent with previous literature [42, 44, 45]. In our context, time coverage is defined as the share of time one's location is known. More specifically, we select panelists observed for at least 20 weeks between January 2020 and September 2022, and showing little variability in time-coverage over time. We use the coefficient of quartile variation [46], to measure the individual variability of time-coverage over time, defined as:

$$\frac{Q_3 - Q_1}{Q_3 + Q_1} < 0.25 \tag{1}$$

Where Q_3 and Q_1 are the 75th and 25th percentiles of the individual's weekly time coverage over time, respectively.

Our final sample includes approximately 21,700 individuals. The median individual time coverage across the data collection span is depicted in Fig. 2. While the median time coverage remains consistent between 75% and 80% for most of the data collection period, there was a notable decline in July and August 2021 due to an unexplained data collection issue.

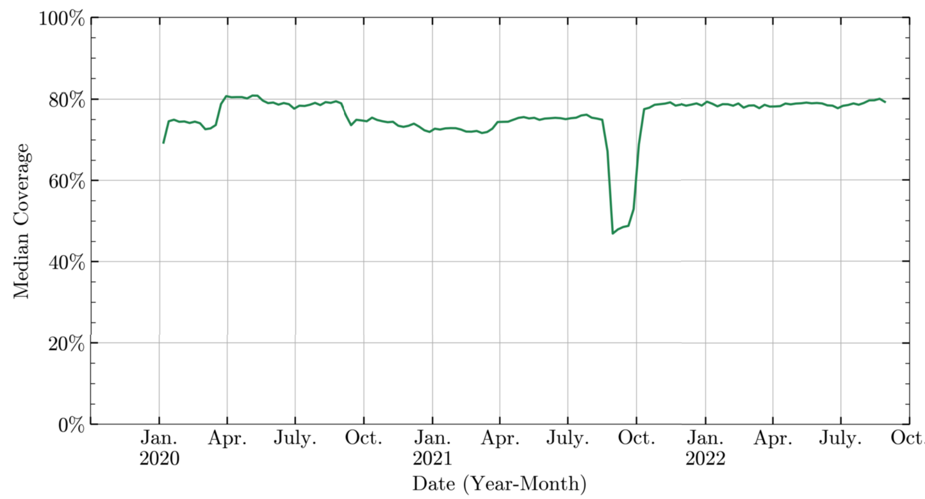

Figure 2 Median weekly temporal tracking coverage across the population as a function of time. A significant drop in coverage occurs in August and September 2021

Table 1 Sample demographic characteristics compared to the US population

	Data (%)	US Population (%)
Female	56.0	50.8
Household Income < 50 K USD	71.1	40.4
White	66.1	72.5
College Degree or More	40.1	38.5

To maintain data integrity, we exclude the data from these two months in our analysis. Further, we find that time-coverage quality was consistent across diverse sociodemographic categories throughout the data collection period.

Table 1 presents a summary of the sociodemographic characteristics of our sample, compared to the U.S. population based on data from the 2019 U.S. census. Notably, our sample is over-representative of females, lower income households, racial minorities and individual with at least a college degree.

We can further process this to compute individual mobility measures of interest (e.g. distance traveled for specific purposes or locations, variability in commute time, dwell time at locations, etc.). In the next section, we present our proposed methodology and the mobility metrics we used to achieve the research objectives.

2.2 Framework and metrics

Travel behavior and its regularity are intricately linked to the many constraints one faces [6, 7, 9]. For instance, transit accessibility, work schedules, and caregiving responsibilities play critical roles in shaping one's travel decisions (e.g. commute timing, frequency, etc.) and their long-term regularity.

However, the COVID-19 pandemic has potentially reshaped this landscape. Beyond its immediate effects on activity patterns, the pandemic-induced relaxation of the spatio-temporal constraints around key activities might be a precursor to newly emerging behaviors emblematic of the post-pandemic "new normal". A case in point is the growing adoption of hybrid work models, which liberate individuals from traditional spatio-temporal

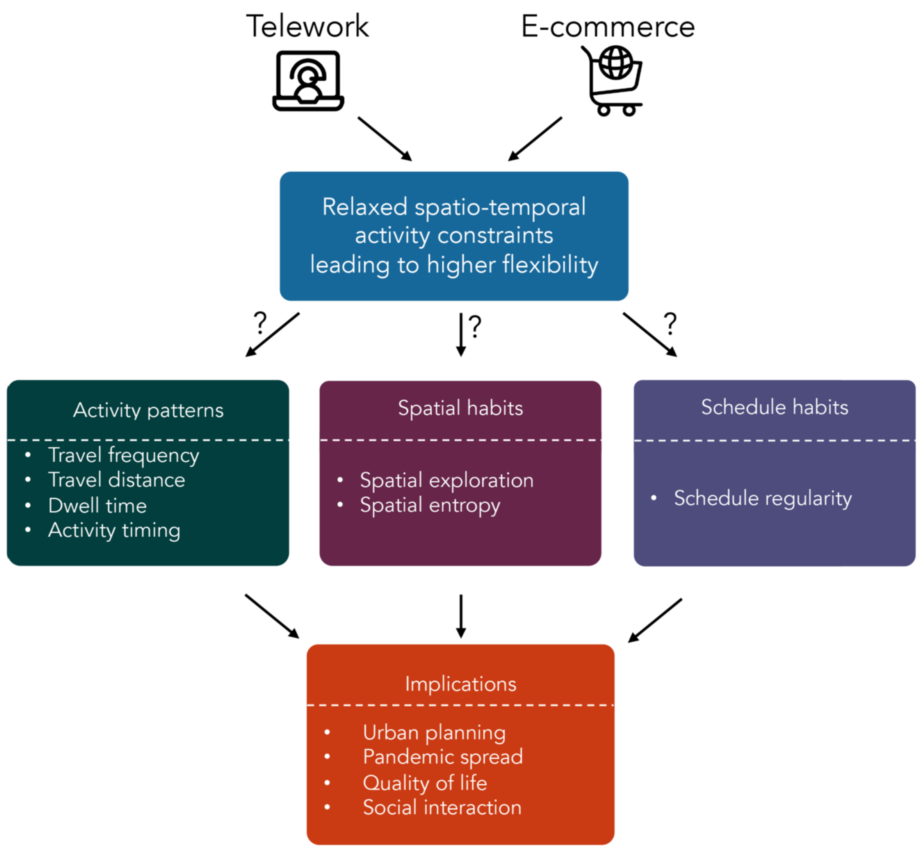

Figure 3 Proposed research framework, highlighting the impacts of relaxed spatio- temporal constraints on human mobility and its possible implications

work constraints. In fact, large shares of workers favor more flexible work arrangements in a post-pandemic world [17, 47]. As a result of this shift, people could start exhibiting new spatial exploration patterns and less structured activity schedules.

Our research objectives are twofold:

- First, to determine if post-pandemic mobility behaviors are different from pre-pandemic baselines
- Second, to assess if post-pandemic mobility behaviors exhibit stability and, if not, identify post-pandemic trends

Our hypothesis in this research is that the relaxation of spatio-temporal constraints following the COVID-19 pandemic have a broader influence on mobility behavior, affecting not just activity patterns, but also spatial and schedule habits. To test this hypothesis, we present a framework (Fig. 3) that goes beyond investigating the impact of the COVID-19 pandemic on traditionally reported mobility metrics (namely, travel frequency, distance traveled, activity duration, and activity timing), and extends to metrics that capture spatial and schedule habits.

In the case of activity patterns and spatial habits, build upon the existing literature, emphasizing the pandemic's long-term effects and understanding what a post-pandemic new normal is shaping up to be. Regarding schedule habits, we propose a new metric capturing the regularity of individual schedules over time, while controlling for day-of-week characteristics. The following sections present, in greater detail, each of these dimensions and the metrics we use to capture their evolution throughout the COVID-19 pandemic.

Activity patterns: First, the loosening of spatio-temporal activity constraints throughout the pandemic can impact activity patterns. For example, individuals with flexible working arrangements can decide take fewer trips or avoid commuting during peak periods. Previous work has explored the impact of the COVID-19 pandemic on many widely reported mobility metrics including trip frequency [20], travel distance [26, 48], and time-use [36]. In this work, we characterize activity patterns by the following quantities:

- *Travel frequency*: We characterize travel frequency by the number of weekly trips taken by an individual.
- *Travel distance*: We use the radius of gyration to characterize the typical distance traveled by an individual [49]. The radius of gyration is defined as:

$$r_g = \sqrt{\frac{1}{n}\sum_{j=1}^{n} \mathrm{dist}(r_j - r_{cm})^2} \tag{2}$$

  Where r_j is a two-dimensional vector of the spatial coordinates of the j^{th} location, and r_{cm} is the center of mass of the locations visited by the individual, $\mathrm{dist}(r_j - r_{cm})$ is the haversine distance between the j^{th} location and the center of mass, and n is the total number of locations visited.
- *Stay duration*: We use dwell time at each POI to measure the typical stay duration of an individual i at any visited location. Dwell-time is a key component of mobility models [14, 50]. Further, as the pandemic has forced many people to stay at home, especially in its early phases, we distinguish between total daily at-home dwell time and out-of-home dwell-time to investigate any possible shifts in dwell-time across different location types. We present results on at-home total stay duration in the main text and include additional results on out-of-home visit dwell-time in the Appendix.
- *Trip timing*: We measure peak demand concentration by identifying the share of trips during the AM peak (i.e. 6-9AM) that fall between 7-8AM.

Spatial habits: Beyond activity patterns, the relaxation of spatio-temporal activity constraints during the COVID-19 pandemic could also reshape individuals' spatial habits. While research suggests individuals balance exploring new places with revisiting known ones [14], the pandemic's influence on this balance is yet to be fully understood. In particular, the relaxation of spatio-temporal activity constraints might redefine how individuals explore their surroundings. Further, while the use of geographical space tends to be uneven, with people spending the majority of their time in a limited number of locations, notably work and home, looser spatio-temporal constraints might alter this distribution, possibly resulting in higher heterogeneity of use of geographical space.

We use the following measures to quantify how the propensity of exploration and exploitation:

- *Spatial exploration*: We use the spatial exploration rate, σ_p [51], which measures the fraction of total visits to new places to capture the propensity for exploration for each individual, defined as:

$$\sigma_p = \frac{S}{N} \tag{3}$$

Where S is the number of unique locations visited and N is the total number of visits made by the individual.

- *Spatial entropy*: We use entropy to measure the heterogeneity of time distribution across geographical space. Spatial entropy has been used in previous works [52–54] and is defined as:

$$H_{\text{norm}} = \frac{-\sum_{i=1}^{N} p_i \log(p_i)}{\log(N)} \tag{4}$$

Where $p_i = \frac{T_i}{\sum_i^N T_i}$ is the probability of finding the individual at location i and T_i is the total time spent at location i, and N is the total number of unique locations visited by the individual. Lower entropy values indicate lower heterogeneity in one's whereabouts.

Schedule habits: Temporally, a loosening of spatio-temporal constraints could induce people to be less habitual in their schedules from week to week. For example, an employee with a hybrid work schedule can decide to commute to their workplace on different days from week to week. We use the cosine similarity to calculate the similarity between any pair of daily schedules. In this context, we describe a schedule by the distribution of time spent across different locations. The cosine similarity is defined as follows:

$$\text{Cosine}(\mathbf{d}_{\mathbf{(i,t,j)}}, \mathbf{d}_{\mathbf{(i,t,k)}}) = \frac{\mathbf{d}_{\mathbf{(i,t,j)}} \cdot \mathbf{d}_{\mathbf{(i,t,k)}}}{\|\mathbf{d}_{\mathbf{(i,t,j)}}\| \cdot \|\mathbf{d}_{\mathbf{(i,t,k)}}\|} \tag{5}$$

Where:

- $\mathbf{d}_{\mathbf{(i,t,j)}}$, $\mathbf{d}_{\mathbf{(i,t,k)}}$ represent the normalized time allocation vectors for the same individual i on day of week t (i.e., Monday, Tuesday, etc.) from distinct weeks j and k.
- $\mathbf{d}_{\mathbf{(i,t,j)}} \cdot \mathbf{d}_{\mathbf{(i,t,k)}}$ represents the dot product of vectors $\mathbf{d}_{\mathbf{(i,t,j)}}$ and $\mathbf{d}_{\mathbf{(i,t,k)}}$.
- $\|\mathbf{d}_{\mathbf{(i,t,j)}}\|$ and $\|\mathbf{d}_{\mathbf{(i,t,j)}}\|$ represent the Euclidean norm (magnitude) of vectors $\mathbf{d}_{\mathbf{(i,t,j)}}$ and $\mathbf{d}_{\mathbf{(i,t,k)}}$, respectively.

The time allocation vectors (i.e., $\mathbf{d}_{\mathbf{(i,t,j)}}$ and $\mathbf{d}_{\mathbf{(i,t,k)}}$ in equation (5)) for an individual i are both L_i-dimensional vectors (where L_i is the number of unique locations visited by individual i, identified from the aggregating individuals' POI locations into geographical locations, see Sect. 2.1) containing the normalized time spent in any of the different locations on any specific day. The cosine similarity measures the cosine of the angle between the two non-zero vectors in the L_i dimensional activity location space, in this context the angle between the vectors representing the allocation of time across geographical space on two distinct days.

We evaluate schedule similarity for the same individual through pairwise daily schedule comparisons to the same type of day (i.e. Monday vs. Monday, Tuesday vs. Tuesday, etc.). Evaluating similarity in this manner controls for characteristics of specific days of week, such as outside social constraints common to the same day of week (e.g. specific commute schedule, recurring social commitments on specific days, care-taking responsibilities, etc.).

This approach builds on the large body of literature addressing intrapersonal travel behavior similarity. Previous works, primarily based on self-reported travel diaries, has explored the depth of variability in travel decisions [9, 55–58], finding a significant degree of intrapersonal variation, the extent of which depends on the nature of travel decisions [9] and socio-economic characteristics [59]. However, these studies overlook the likelihood that travel habits, influenced by societal constraints, can differ based on the specific day of the week. More specifically, they do not account for possible shared characteristics between observations on the same day of week, at most comparing weekdays to each other and weekend days to each other [9, 58]. Accounting for day-of-week characteristics is crucial in understanding the regularity of schedules, as societal obligations and constraints are often tied to specific days. For example, a parent might have a consistent obligation to drive their child to an after-school activity every Wednesday afternoon, while Thursdays might involve weekly parent-child community group meetings, leading to distinct schedules on those days, even if they are both weekdays.

The cosine similarity has been used extensively in the human mobility literature, measuring similarity in individuals' activity spaces over time [42], clustering individuals based on their mobility patterns [60–62], and measuring similarity of neighborhoods according to their mobility patterns [63], among many others [64]. To ensure that our results are not an artifact of our choice of metric, we use other metrics proposed by Lee et al. [65] and find that our results remain consistent.

2.3 Analysis approach

On January 21, 2020, the United States reported its first COVID-19 case in the state of Washington. By late February, concerns about community spread intensified. In response, several states declared states of emergency in early March, a move that many states would soon emulate. On March 13, 2020, the Federal government declared a national emergency, mobilizing federal resources to manage the pandemic. By mid-March, many states and local jurisdictions had initiated measures such as school closures, large gathering restrictions, and social distancing protocols. By the end of April and into May, while most states still had declared emergencies and stay-at-home orders in place, several began outlining phased reopening plans, balancing economic needs with public health concerns. By the end of 2020, a range of vaccines had become available, marking a pivotal turning point in the pandemic. This development heralded the start of a nationwide vaccination drive in early 2021. By May 2021, vaccinations had become widely available in the US. By end of 2021, approximately 83% of U.S. adults had already received at least one vaccine shot [66]. Figure 4 presents key milestones throughout the COVID-19 pandemic in the U.S., including the number of reported cases and significant markers throughout the pandemic, such as state reopenings, vaccination rollouts, and the emergence of COVID-19 variants.

With this backdrop in mind, we investigate the impact of the COVID-19 pandemic and its associated loosening of spatio-temporal activity constraints on activity patterns, spatial habits, and schedule habits. To achieve our research objectives, we proceed as follows:

- To determine if post-pandemic mobility behaviors are different from pre-pandemic baselines: We compare mobility metrics across three pivotal periods: February 2020 (representing pre-pandemic mobility), February 2021 (one year into the pandemic), and February 2022 (two-year outlook, after wide vaccination). This allows us to discern shifts and continuities in mobility trends over these critical junctures.
- To assess if post-pandemic mobility behaviors exhibit stability and, if not, identify post-pandemic trends: We analyze metrics from May 2021, marking the period post widespread vaccine availability, and compare them to May 2022. This comparison helps decipher whether behavioral changes observed after the vaccine rollout have persisted or are continuing to evolve.

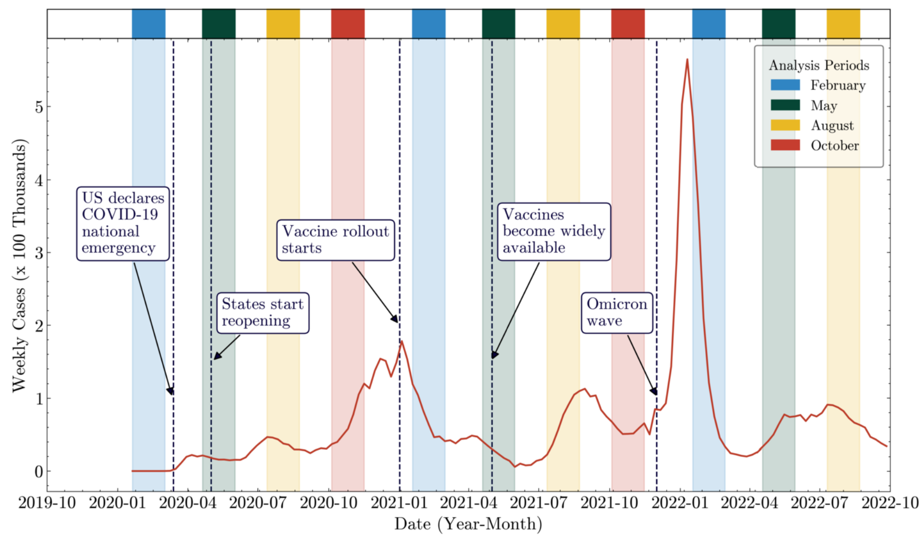

Figure 4 Timeline of weekly COVID-19 cases in the United States and key pandemic milestones

We compute our proposed metrics at key times throughout our data collection period, shown with colors vertical stripes in Fig. 4 and employ 2-tailed t-tests to compare mobility metrics across key periods. By consistently comparing data from similar months across different years (e.g., February 2020, 2021, and 2022), we aim to negate the influence of any seasonal factors that might affect mobility, such as weather patterns, holidays, or school cycles, ensures that any observed differences in mobility patterns can be more confidently attributed to the pandemic's influence. For our first objective, we use data from February 2020, 2021, and 2022 (shown in blue stripes). For our second objective, we use data from February 2021 and February 2022 (shown in blue stripes), as well as May 2021 and May 2022 (shown in green stripes). The other time periods provide us with further indication on how each of the metrics evolved throughout the pandemic and their levels post-pandemic. We should note the deliberate omission of August 2021 due to the data coverage quality issues summarized in Sect. 2.

3 Results

Within our framework, we identified seven metrics to investigate how the COVID-19 pandemic and its associated relaxation of spatio-temporal activity constraints has impacted activity patterns. The following subsections summarize the results of three categories of metrics identified in the framework presented in Fig. 3.

3.1 Activity patterns

In this section, we present our analysis results of four key metrics identified to understand the impact of the relaxation of spatio-temporal activity constraints through the COVID-19 pandemic on activity patterns. We summarize the results in Fig. 5.

Figure 5a summarizes the evolution of the average number of weekly trips throughout the COVID-19 pandemic. We observe the initial dip in the number of weekly trips between February 2020 and May 2020 from 22 trips to approximately 20.5 trips. While this decrease might not seem as significant as what was reported in the literature [26], it reflects

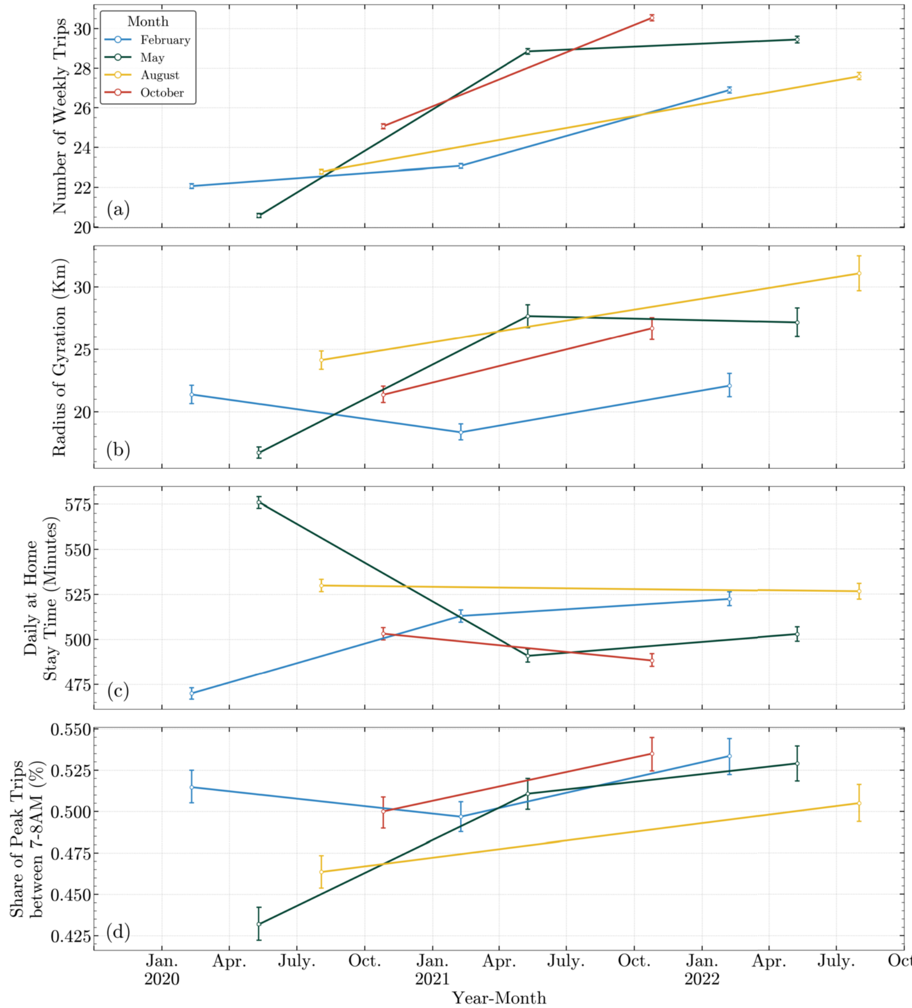

Figure 5 Evolution of activity patterns throughout the COVID-19 pandemic. (a) weekly trips, (b) radius of gyration, (c) daily at-home stay duration between 6AM-9PM, (d) share of peak trips between 7-8AM. Error bars represent the 95% confidence interval around the estimated population means. ($N \approx 21{,}700$ individuals)

conditions after several states have started reopening [67]. Since then, we observe a continuous increase in the number of weekly trips individuals take all throughout the pandemic. When comparing post-pandemic conditions (February 2022) to pre-pandemic conditions (February 2020), we observe that the number of trips has recovered to its pre-pandemic baseline (as early as February 2021), with an average of 26.9 weekly trips in February 2022 compared to 22 weekly trips in February 2020 ($p < 10^{-3}$). Further, we observe an increasing trend in the number of weekly trips taken after the wide vaccine availability (May 2021 vs. May 2022, $p < 10^{-3}$).

Figure 5b summarizes the evolution of the radius of gyration throughout the pandemic. We observe a decrease in the range of the radius of gyration in the early phases of the pandemic (between February 2020 and May 2020), from 21.5 to 16.7 km ($p < 10^{-3}$), indicating that people have reduced their mobility's spatial range, consistent with the observation that people were spending most of their time at home, and when traveling, traveling to areas close to their home location. We observe a continuous recovery of the average radius of gyration after the initial phases of the pandemic, despite the seasonal fluctuations, consistent with other findings in the literature [11]. In February 2021, shortly after the beginning of the vaccine rollout in the U.S., the radius of gyration was still lower than its pre-pandemic levels in February 2020 ($p < 10^{-3}$). However, in February 2022, the radius of gyration has recovered to its pre-pandemic level ($p = 0.23$). Post-pandemic, we observe that the radius of gyration is stable between May 2021 and May 2022 ($p = 0.49$). In October 2021 (i.e. after wide availability of vaccines), we observe that people exhibit higher radius of gyration than October 2020. Similarly, in August 2022, we notice larger radius of gyration compared to August 2020, likely due to the recovery of out-of-home travel. Further, we observe that the radius of gyration shows strong seasonal patterns, with summer months exhibiting higher radius of gyration levels than winter months, possibly due to summer travels. When juxtaposed to the evolution of trip frequency during the pandemic, we observe that even as people started more trips in 2021 compared to pre-pandemic, the spatial extent of such trips has not expanded beyond its pre-pandemic ranges.

Next, we turn our attention to the evolution of dwell-time throughout the pandemic. Dwell-time is a key parameter for mobility models [49, 50]; in each displacement, an agent chooses a destination and a dwell-time from observed dwell-time distributions. Such dwell-times have been shown to be different for different destination types [42]. Given the COVID-19 context, we present results summarizing the evolution of dwell-times for inferred home in the main text and include results on out-of-home dwell-times in the Appendix. We note that our home dwell-times capture the total duration of stay at home, as opposed to per-visit dwell-times.

First, Fig. 5c summarizes at-home total stay times, focusing only on the core active hours of the day between 6AM and 9PM. In the early phases of the pandemic, we observe a sharp increase in the at home daily dwell-time, from 7.8 hours to 9.6 hours (May 2020 vs February 2020, $p < 10^{-3}$), mostly as a result of people spending more time at home. This finding consistent with previous literature findings [36] and representative of the overall observations that large shares of the population spent more time at home during the early phases of the pandemic either in compliance with restrictive mobility measures or in fear of the contracting the virus. While an approximate average two-hour increase in the pandemic might seem as an underestimate, it exhibits large heterogeneity, with the 75^{th} percentile being as much as 12 hours between 6AM and 9PM in May 2020. Unlike the radius of gyration, daily at-home stay times never recovered to their pre-pandemic levels. Looking in the long-term, post-pandemic at-home daily stay times remain higher than their pre-pandemic baselines, with people spending almost one more hour (55 minutes) at home in post-pandemic compared to pre-pandemic (February 2022 vs. February 2020, $p < 10^{-3}$) They also exhibit stability post-pandemic, where the average dwell-time at home in May 2022 is 12 minutes more than the average at home stay time in May 2021, albeit this difference is statistically significant ($p < 10^{-3}$) as a result of our large sample size.

On the other hand, out-of-home visit dwell-times exhibit the opposite trend, with people spending less time per visit at out-of-home locations in post-pandemic that never recovered to its pre-pandemic levels (see Appendix for details). These observed diverging patterns in the at-home and out-of-home dwell-times could have implications on the refinement of mobility models [50], where the selection of sampling distribution of dwell-times could be conditional on the destination an agent chooses.

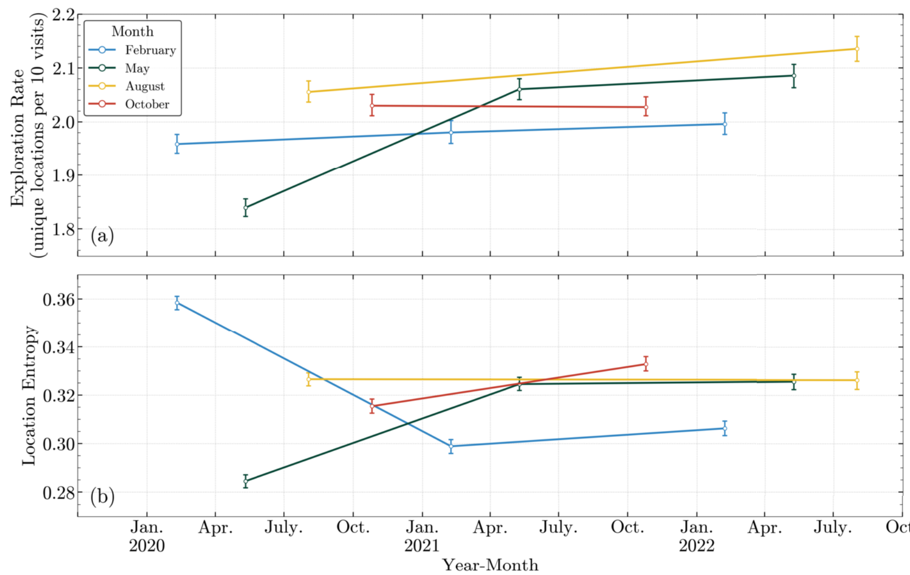

Figure 6 Evolution of spatial habit patterns throughout the COVID-19 pandemic: (a) exploration rate (σ_p), (b) spatial entropy (between 6AM-9PM). Error bars represent the 95% confidence interval around the estimated population means. ($N \approx 21{,}700$ individuals)

Beyond trip frequency, distance traveled, and dwell-time, timing of trips is important in the predictability of demand for planning purposes. We hypothesize that as people experienced looser temporal activity constraints, congestion levels during peak periods would reduce and peak demand would flatten. To test this hypothesis, we investigate the evolution of the share of AM peak trips (6-9AM) taken between 7-8AM and summarize the results in Fig. 5d. We find that in the early phases of the pandemic, this share decreased from approximately 52% to 43%, indicating a flattening of the AM peak travel, and consistent with previous findings from the literature [68]. However, going beyond the early phases of the pandemic, we find that this share recovers to its pre-pandemic levels in February 2022, with 53% of the AM peak trips occurring between 7-8AM, compared to 52% in February 2020, although this difference is statistically significant ($p < 0.05$). Peak demand patterns remain stable in the post-pandemic times, with trips occurring between 7-8AM being 51% of AM peak demand in May 2021, compared to 53% in May 2022, although the difference is statistically significant in our analysis ($p < 0.05$). Overall, the share of AM peak trips (6-9AM) taken between 7-8AM is higher in 2021 and 2022 compared to the early phases of the pandemic in 2020 (May, August, and October). This finding indicates that despite initial hopes that the pandemic would result in less intense peak periods, old demand patterns have returned to their pre-pandemic levels.

3.2 Spatial habits

In the previous section, we presented findings showing the evolution of conventional metrics used to understand human mobility throughout the pandemic. These metrics alone are not enough to understand the complexities of human mobility.

In this section, we explore how the COVID-19 pandemic and its associated relaxation of spatio-temporal activity constraints have reshaped spatial habits. Figure 6 presents our results.

Figure 6a summarizes how exploration behavior has changed throughout the COVID-19 pandemic. Before the pandemic, people explored approximately 1.96 new locations for every 10 visits. This exploration rate dropped during the early phases of the pandemic (May 2023) to approximately 1.84 new locations for every 10 visits ($p < 10^{-3}$). Similarly to other metrics, lower exploration is associated with people going to a limited set of locations to comply with public health measures or in fear of contracting the virus. We find that the exploration rate has returned to its pre-pandemic levels, with people exploring 2 new places for every 10 visits, compared to 1.96 visits for every 10 visits before the pandemic, although this difference is statistically significant ($p = 0.007$), and corroborating findings from previous research comparing exploration rates in 2021 compared to 2019 [69]. When addressing post-pandemic stability in exploration patterns, we find that post-pandemic exploration patterns show stable patterns (May 2021 vs. May 2022, $p = 0.14$). Overall, range of change in the exploration rate throughout the pandemic has not been large, shifting between 1.85 and 2.14 new places every 10 visit. Further, exploration patterns show seasonal fluctuations, with summer months showing higher explorative patterns, likely due to people traveling and visiting newer places.

The distribution of time across space has been shown to be uneven, primarily because of work and home being dominant locations in one's life. As the spatial requirements for work become more relaxed, it remains to be seen whether people start distributing their time across the geographical space. As presented in the methods section, we use spatial entropy to understand the heterogeneity of distribution of time across the geographical space throughout the COVID-19 pandemic. Figure 6b summarizes the average spatial entropy across the population throughout the COVID-19 pandemic, where higher entropy indicates higher heterogeneity in distribution of time across the geographical space. We find that during the early phases of the pandemic, spatial entropy has decreased by 20% ($p < 10^{-3}$), indicating the decreasing heterogeneity in one's whereabouts. Further, well into the pandemic, we observe that spatial entropy has not recovered to its pre-pandemic levels, remaining 15% lower than its baseline value January 2020 ($p < 10^{-3}$). Post-vaccination, we find that spatial entropy has remained stable when comparing May 2021 to May 2022 ($p = 0.61$).

As a summary, we find that while exploration rates have returned to their pre-pandemic baselines, there is evidence for less heterogeneity in the distribution of time across geographical space.

3.3 Schedule habits

Beyond spatial habits, understanding the regularity of routines from week to week is key in understanding the predictability of human behavior. Within the COVID-19 context, we hypothesized that as people experience less spatio-temporal activity restrictions, they would tend to exhibit less similarity in their day-of-week schedules over time. Further, we suggest that controlling for day-of-week in evaluating intrapersonal schedule variability is critical in understanding predictability of human behavior, as social constraints are often associated with set temporal constraints on distinct days.

Figure 7 summarizes the cosine similarity of day-of-week distribution of time and illustrates that schedule habits show strengthening in the early phases of the COVID-19 pandemic (February 2020 vs. May 2020, $p < 10^{-3}$), likely as a result of people spending large shares of time at home. However, contrary to our initial hypothesis, individuals exhibit stronger schedule habits in post-pandemic compared to pre-pandemic, with people

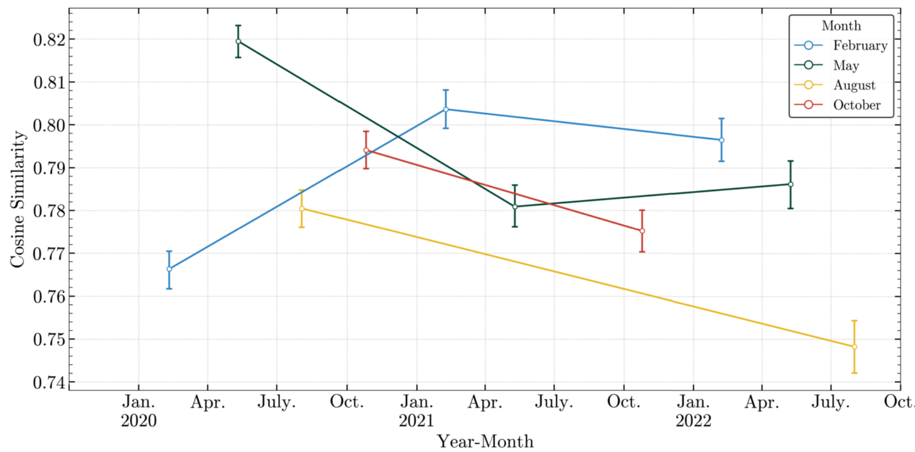

Figure 7 Day-of-week schedule cosine similarity throughout the COVID-19 pandemic. Schedule similarity is calculated between 6AM-9PM. Error bars represent the 95% confidence interval around the estimated population means. ($N \approx 21{,}700$ individuals)

showing stronger habits in February 2022 compared to February 2020 ($p < 10^{-3}$). Additionally, we also find evidence for stability in schedule habits post-pandemic (May 2021 vs. May 2022, $p = 0.14$).

The lack of evidence for less structured schedules is surprising, as previous works find strong evidence that workers favor more flexible work arrangements in a post-pandemic world [47]. Our finding indicates that while people prefer flexibility, they might take advantage of it by setting an individual schedule that remains strong over time. Further, our finding does not necessarily mean that people returned their pre-pandemic behaviors, but show that while they might have adopted new behaviors, they exhibit strong habits in such behaviors.

3.4 Relationship between spatial habits and schedule habits

In the previous sections, we find evidence for changes in both spatial and schedule habits of human mobility post-pandemic. In this section, we investigate the association between these two aspects of mobility habits (i.e. diversity in spatial habits and schedule regularity). More specifically, we present this association at two distinct points in time, February 2020 and February 2022. Figure 8 presents the contour plots for the kernel density estimation of the distribution of cosine similarity (schedule habits) vs. spatial entropy (spatial habits) at three distinct levels of the probability density function.

First, regardless of the time period, we observe a negative relationship between spatial entropy and cosine similarity. This indicates that, on average, people with higher spatial diversity are likely to exhibit less regular day-of-week schedules across weeks. Further, we observe higher heterogeneity in cosine similarity (schedule habits) at higher levels of spatial entropy indicating that despite having high spatial diversity, distinct individuals can exhibit a wide range of schedule regularity. Second, we observe a shift in the population distribution between February 2022 and February 2020, highlighting a coupled shift in both dimensions, with the population shifting more towards both less spatial diversity and stronger schedule habits.

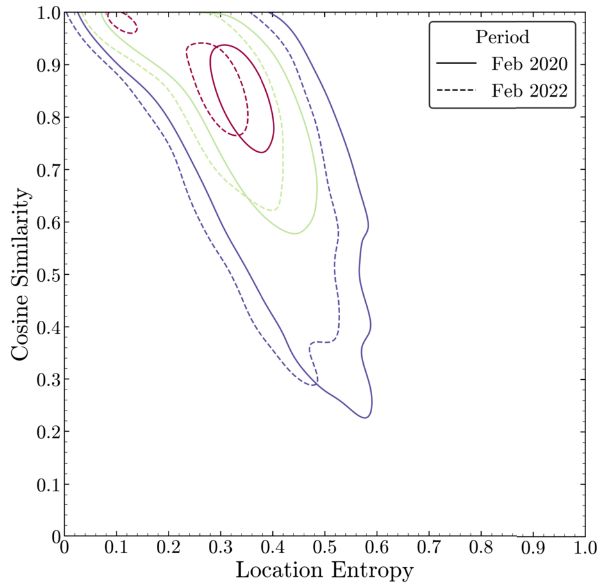

Figure 8 Correlation between cosine similarity and spatial entropy in February 2020 (continuous) and February 2022 (dashed line)

4 Conclusion

In this study, we contribute to the extensive body of literature aiming to understand the impacts of the COVID-19 pandemic on human mobility behavior. Motivated by the relaxation in spatio-temporal constraints of key activities such as work and shopping, we go beyond investigating the impacts of the pandemic using traditionally reported key metrics since these metrics do not convey the full complex picture of human mobility behavior and how it was reshaped.

Using passively tracked POI data from a panel of smartphone users in the U.S. between January 2020 and September 2022, we propose an analytical framework that distinguishes the impacts of the relaxation of spatio-temporal activity constraints on activity patterns, spatial habits, and schedule habits. Within this framework, we use a suite of metrics each designed to capture distinct aspects of human mobility. Most notably, we propose a new metric to measure schedule habits, more specifically to measure the similarity of weekly schedules over time, controlling for differences between different days of the week. In doing so, we also contribute to the large body of literature on intrapersonal variability in mobility behavior.

Our findings paint a complex picture, as summarized by Fig. 1. Our data reveals that, while there was a significant impact on multiple aspects of human mobility during the early phases of the pandemic, such impacts were not permanent across all explored metrics. In terms of activity patterns, we find that with the exception of dwell-times, key aggregate mobility metrics have recovered to their pre-pandemic baselines, even exceeding them by 2022 as in the case of number of weekly trips. Dwell-times have been reshaped, with out-of-home visit dwell-times still remaining lower than their pre-pandemic baselines. Further, we find that despite exploration patterns being on average similar to their pre-pandemic baselines, there is less heterogeneity in people's distribution of time across space. Surprisingly, our data reveals the strengthening of schedule habits in a post-pandemic world, challenging our initial hypothesis that people would take advantage of looser spatio-temporal constraints and exhibit more variable schedules from week to week. We also document the relationship between spatial and schedule habits, showing that higher levels of spatial entropy (i.e. spatial diversity) are associated with lower schedule regularity.

These findings, however, are not without limitations. First, this research is based on data between January 2020 and September 2022, and is focused on US participants. We strongly encourage other researchers to replicate this analysis on data from outside the US and well before 2020 and beyond 2022 to help strengthen our findings and make them more generalizable. Second, although we have used well-established mobility metrics in drawing our conclusions, our analysis might still suffer from possible biases relating to our data's sociodemographic profile and possible uncertainties in the data collection and location inference algorithms. Given the documented disparate impacts of the COVID-19 pandemic across different socio-demographic groups, future research should explore whether our findings hold across socio-demographic groups. Third, our new proposed metric to capture differences between weekly schedules only accounts for time distribution across space and does not account for activity order within the day. Future work should expand on this metric to account for activity order, as such analysis would be relevant in contexts where people maintain the same time allocation patterns but shift their activity orders (i.e.: shifting working hours to a different time window).

Appendix

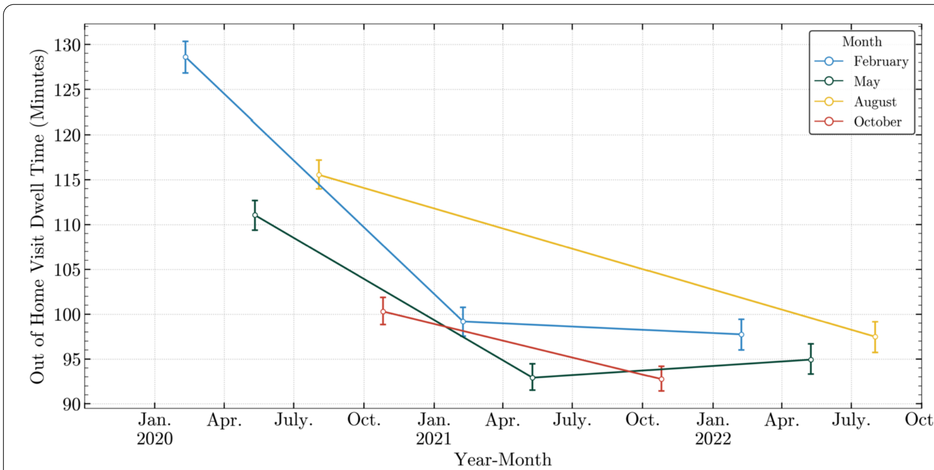

Figure 9 Evolution of out-of-home dwell-time throughout the COVID-19 pandemic. The error bars represent the 95% confidence interval around the population mean. ($N \approx 21{,}700$ individuals)

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List of abbreviations
POI, Point Of Interest; DBSCAN, Density-Based Spatial Clustering of Applications with Noise; NPI, Non-Pharmaceutical Intervention; CDC, Center for Disease Control; CDR, Call Detail Records; LBS, Location Based Service; MSA, Metropolitan Statistical Area.

Data availability
The data used in this research was provided by Similarweb for the exclusive use in this research and are not publicly available. We do not plan on making this data available since it was restricted for the use in this research only.

Code availability
Not applicable.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
All authors declare that they have no conflicts of interest.

Author contributions
MAB: Conceptualization, Methodology, Data curation, Formal Analysis, Writing—original draft, Writing -review & editing, Funding acquisition. JW: Conceptualization, Methodology, Supervision, Writing—review & editing MCG: Conceptualization, Methodology, Supervision, Writing—review & editing. HO: Data curation, Writing—review & editing. All authors read and approved the final manuscript.

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