Title

A longitudinal analysis of the COVID-19 effects on the variability in Human Activity Spaces in Quito, Ecuador

Keywords

Google Location History (GLH), Human Activity Space (HAS), Longitudinal Data, GPS, COVID-19

Abstract

The COVID-19 pandemic has had a huge impact on human activities due to lockdowns or travel restrictions to preserve public health and decrease the workload of hospitals. Therefore, human activities spaces (HASs) were deeply affected worldwide, but to an extent that is hard to quantify properly. This paper presents a longitudinal analysis of HASs in Quito, Ecuador, before and during the COVID-19 pandemic. Using location data collected through Google Location History (GLH) from the Google Maps application, we compute weekly people's activity point locations (APLs) from a convenience sample of 263 participants, mainly composed of university staff members, considering only weeks with at least five days of data. These APLs are then used to measure the HASs using the confidence ellipses and the minimum spanning trees. Finally, we perform a weekly intra-personal and inter-personal variability analysis of the HASs using a random intercept model, considering (a) the size of HASs as the dependent variable and (b) the levels of restrictions due to the pandemic and the participants' demographics as independent variables. The results reveal that HASs are strongly affected by the intensity of non-pharmaceutical interventions (NPIs) (Social distancing, quarantines, lockdowns, travel restrictions or closure of schools and workplaces) and the composition of the socio-demographic groups. We also demonstrate that the disruptive effects of NPIs on human mobility were reflected in the decrease in trip durations in conjunction with a drop in visited locations as individuals

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only engage in essential neighbouring activities, implying substantial variations in the size and extent of HASs.

Introduction

The COVID-19 pandemic has impacted human activities worldwide, resulting in profound changes in mobility patterns and altered travel behaviours on both local and global scales. As researchers were confronted with the multifaceted impacts of the COVID-19 pandemic, movement metrics have emerged as crucial indicators to study, model, and mitigate the impacts of the COVID-19 pandemic (Noi et al., 2022). Notably, stringent lockdowns and the need for physical distancing have necessitated drastic travel restrictions and a reduction in travel demand, reshaping the dynamics of movement to curtail disease transmission. The pandemic has highlighted the vulnerabilities of established public transport systems and shared mobility solutions, accelerating the shift to more sustainable urban mobility alternatives, such as micro-mobility and active transport (Abduljabbar et al., 2022; Zhou, Liu, et al., 2021).

Latin American countries experienced the onset of COVID-19 slightly later than European countries, affording them a brief window for emergency preparedness and response. However, these countries, characterised by limited healthcare resources and socio-economic disparities, swiftly implemented stringent measures to counter the spread of the virus. While efforts to bolster healthcare infrastructure were made, challenges in tracing and tracking persisted. The pre-pandemic conditions of high informal employment and social inequalities in these countries have undermined the effectiveness of the countries' responses to the pandemic and their ability to contain the spread of COVID-19 (Benítez et al., 2020). Although the perceived impacts of COVID-19 influenced the shift from public transport to private modes, they failed to induce a significant transition to more sustainable active transport modes (Vallejo-Borda et al., 2022).

An illuminating Colombian study used open data sources, including motion data from Facebook and public mobility reports from Google and Apple, to determine the dynamics of population mobility during the period after the appearance of COVID-19. The mobility of the population decreased drastically during the period of mandatory quarantine and gradually rebounded over time as a reflection of changing displacements and evolving social distancing measures (Solis Pino et al., 2022). This evolution highlighted a pertinent concern for vulnerable segments of the population, particularly low-income individuals who faced heightened exposure to contagion due to their reliance on daily sustenance. These individuals encountered disparities in access to non-work-related activities and essential services, further exacerbating inequalities (Guzman et al., 2021). As exposure to COVID-19 increased, the number of trips, travelling miles, and overnight trips started to bounce back to pre-COVID levels, while the incidence of working from home remained stable and did not tend to return to pre-COVID levels. The increase in new COVID cases significantly impacts the number of work trips in the low socio-economic segments but has little impact on the high. The fewer medical resources there are, the fewer mobility behaviour changes individuals in the low socio-economic segments will undertake (Xi et al., 2023).

In the Caribbean Sea, Puerto Rico contended with significant travel restrictions to the island since March 2020, which heavily influenced residents' travel behaviours. Surprisingly, it was found that the elderly population was much more likely to travel during the pandemic, despite being more vulnerable to COVID-19. Also, during the holiday season in 2020, some socioeconomically disadvantaged populations were more likely to be travelling (Carter & Tao, 2023). The existing literature has emphasised multimodal transportation, underscoring the pandemic's role in fostering a comprehensive understanding of travel demand and its implications. This reflects the increasing interest of researchers in understanding how the sanitary crisis impacts the use of all modes of transportation, ranging from traditional transport systems to innovative shared mobility solutions. COVID-19 has underscored the critical role of multimodal transportation as an integral facet of sustainable urban development, accompanied by the recognition of telecommuting as a pivotal strategy (Benita, 2021).

In Ecuador, stringent COVID-19 containment measures were implemented in mid-March 2020 following the State of Health Emergency declaration by the national government's National Health System (Ministerio de Salud Pública, 2020). During the first weeks of the lockdown, inhabitants' freedom of transit and mobility in all country provinces were entirely restricted. Only health personnel, national police and armed forces could circulate to guarantee essential services, food, and supply chains.

This new lifestyle generated considerable changes in people's daily mobility (Toger et al., 2021), travel behaviour (Costa et al., 2022; Lee et al., 2023; Paul et al., 2022), transportation systems used (Borkowski et al., 2021; Rahmat & Khoo, 2022; Zafri et al., 2023), travel demand (Shemer et al., 2022), travel distances (K. Chen & Steiner, 2022; Shende et al., 2023), route choice (Marra et al., 2022), commuting travels (Balbontin et al., 2021) and jobs-housing relationships (R. Chen et al., 2023). Many travel and commuting patterns compared to the pre-COVID-19 era changed. A noticeable fear of viral transmission in public transportation or ride-sharing vehicles has reduced the usage while increasing the use of the private car, revealing an impact on mode choice preferences during the COVID-19 pandemic. Air transport is one of the most hit sectors because all international and local flights are cancelled. Shopping trips have been observed to be among the most highly participated ones during the pandemic. These trips can be considered trips for buying essential grocery items. E-commerce activities and delivery freight transport have increasing importance in daily life. Possible long-term effects of COVID-19 on activity-travel behaviour can be expected from economics, psychology, sociology, and geography perspectives. Specifically, that peak demand among car and public transport users may be lower than if the pandemic would never happen (van Wee & Witlox, 2021).

In the post-pandemic era, almost all businesses and agencies in the public and private sectors maintain some work-from-home policy. Additionally, many companies closed their offices to switch to a virtual workplace for economic benefits. Many retail stores have permanently closed and are operating solely as online businesses. Notably, policies such as telecommuting and remote learning have emerged as potent tools for managing travel demand, offering a unique opportunity for rigorous evaluation (Shemer et al., 2022). It is important to have a clear idea of how COVID-19 changed mobility patterns and what policies must be taken to minimise viral transmission as well as develop a sustainable transportation system.

The curtailment of social interactions significantly changed both the frequency and nature of out-of-home activities. As a result, people made fewer long-distance trips, used public transportation less frequently, and shifted towards activities such as walking, running/cycling (in case of short distances), or travelling by motorcycle or private car if available (De Vos, 2020). It is important to recognise that travel behaviour and accessibility are not confined to the domain of urban transport planning; they are linked to broader urban and land-use planning initiatives. Thus, the role of land-use and urban planning is key in redressing social and spatial inequalities within cities (Guzman et al., 2021). The heterogeneous mobility response of individuals across socio-economic segments to COVID-19 waves provides insights into the equitable transport governance and resiliency of the transport system in the "post-COVID" era (Xi et al., 2023). Understanding the effects of the pandemic on mobility is essential to help mitigate the problems arising from this crisis while also providing an opportunity for implementing sustainable policies in the post-pandemic period (Oestreich et al., 2023). This paper aims to quantify these changes in terms of activity spaces and to determine which factors have the largest impact.

At the core of urban and transport planning lies a fundamental understanding of human activity spaces (HASs), which encapsulate the two-dimensional geographic bounds (longitude and latitude) within which people engage in daily activities. These activity spaces encompass a range of frequently visited Activity Point Locations (APLs) or Points of Interest (POIs), such as homes, workplaces, educational institutions, and recreational venues (see, e.g. Fig. 1). Effectively mapping and comprehending these spaces are crucial for shaping public transit networks and addressing urban challenges like spatial inequality, crime, and health disparities (Cagney et al., 2020).

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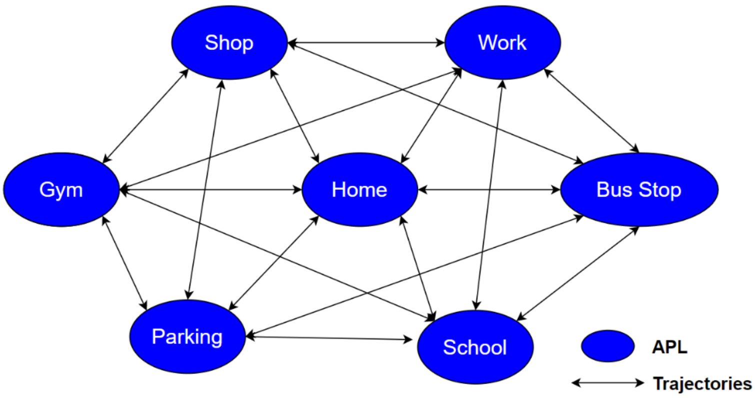

Fig1. Schematic representation of a HAS example. The ellipses represent people's APLs, and the arrows are the potential trajectory connections in daily life. The HAS comprises APLs and connections.

Depending on personal, economic, social, health and cultural factors, HASs vary between different persons. This variability can be addressed from an inter-personal (between-person) and intra-personal (within-person) perspective. Inter-personal behaviour is the external expression of intrinsic socio-demographic characteristics of a person; it depends on each personality. On the other hand, intra-personal behaviour is controlled by the requirements and desires of persons and governed by a set of constraints, typically examined with space-time prisms from a geographical standpoint (Kuijpers, 2017) and the space and time where a person performs activities define the intra-personal behaviour (Dharmowijoyo et al., 2014; Gadermann & Zumbo, 2007; Kitamura et al., 2006; Zhou et al., 2021).

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The HAS variability has been analysed daily, weekly, and monthly (Järv et al., 2014; Srivastava & Schönfelder, 2003). These studies used different techniques to measure the size of activity spaces, as given hereafter:

- *The extension of action space* is represented by the second moment of the Euclidean distance of the APLs with respect to a fixed point, usually the home location (Susilo & Kitamura, 2005);
- *The confidence or standard deviational ellipse* is represented by the smallest possible sub-area in which the population should be found with a given probability, usually 95%. This area is an indicator of the dispersion of APLs visited over a specific period.
- *The kernel density* is represented by an area, most likely a HAS. It relates APLs to the frequency of their corresponding visits.
- *The minimum spanning networks* are represented by the structure and size of the routes chosen by persons to connect their APLs (Schönfelder & Axhausen, 2003a, 2003b).

Studies using these techniques incorporate socio-demographic factors to explain HASs variability. Their findings indicate temporally stable and compact daily activity-travel patterns, more routines during the working days and more dispersion during weekends. Furthermore, socio-demographic factors such as socio-professional status, age, gender, private car use, residential location, household size or workplace have significant effects.

So far, HASs variability over various time periods, that is, days, weeks, or months has been reported in the literature. However, HASs with longitudinal data have not been deeply analysed (Schönfelder & Axhausen, 2002). The main problem is the high cost and time required to collect longitudinal data. However, thanks to the widespread availability and affordability of mobile devices (Townsend, 2000; Wang et al., 2018), it is now possible to study the HAS with data collected over long periods using sensors, mainly GPS (Xu et al., 2021). In the era of low-cost mobile internet services (Korpilo et al., 2017), GPS tracking people's location using mobile devices has become common in the telecommunications industry. In addition, software providers such as Google have built strong leadership in collecting GPS data, for example, the Location History feature that Google introduced in 2009 (9to5Google, 2019). Once a person activates the Google Location History (GLH) option in the Google Maps application (Google, 2021a), Google will then collect detailed location information and provide complete and continuous human mobility data (D. Cools et al., 2021) even when a person isn't using a specific Google service. Data collected with the GLH has an acceptable spatial and temporal resolution to identify people's APLs, which requires a continuously active mobile device's GPS (Macarulla Rodriguez et al., 2018). Data provided by GLH can be combined with complementary socio-demographic information through personal surveys to allow an objective longitudinal analysis of social and spatial behaviour over long periods (Licoppe et al., 2008).

This paper illustrates how much data collected by the GLH is unquestionably a vital data source for HASs research. The data collected over time by Google makes it possible to identify APLs longitudinally with acceptable accuracy. Based on that, we can compute HASs and develop models to analyse them. In this regard, we use a linear mixed-effects model to investigate the influence of lockdowns and socio-demographic factors on the weekly variability of HASs in Quito-Ecuador. We also highlight which factors have substantial effects on HASs variability. The motivation behind this study is driven by the scarcity of comprehensive big data and longitudinal analyses in previous research. In Latin American and developing countries, the exploration of travel behaviour changes induced by COVID-19 remains limited. The work presented here introduces a methodological blueprint for analysing HASs in Ecuador, potentially serving as a robust decision-making tool for governmental bodies. By integrating socio-demographic influences on mobility patterns, this study offers a comprehensive approach to understanding and managing urban movement. Furthermore, the release of an open dataset (Moncayo-Unda et al., 2022) enhances the scientific community's arsenal for scrutinising travel behaviour patterns using anonymous data.

Materials and Methods

Study area

This paper analyses the variability of human activity spaces (HASs) in the Metropolitan District of Quito. Quito is the capital of Ecuador, located in the northern centre of the country at 2,800 metres above sea level in the Andes Mountain range. It comprises 9 zonal administrations and 65 parishes, 32 urban, 33 rural and suburban entities. It has about 2.8 million inhabitants (INEC, 2020) and an area of approximately 4,230 square kilometres (Instituto Metropolitano de Planificación Urbana, 2018). (Fig. 2).

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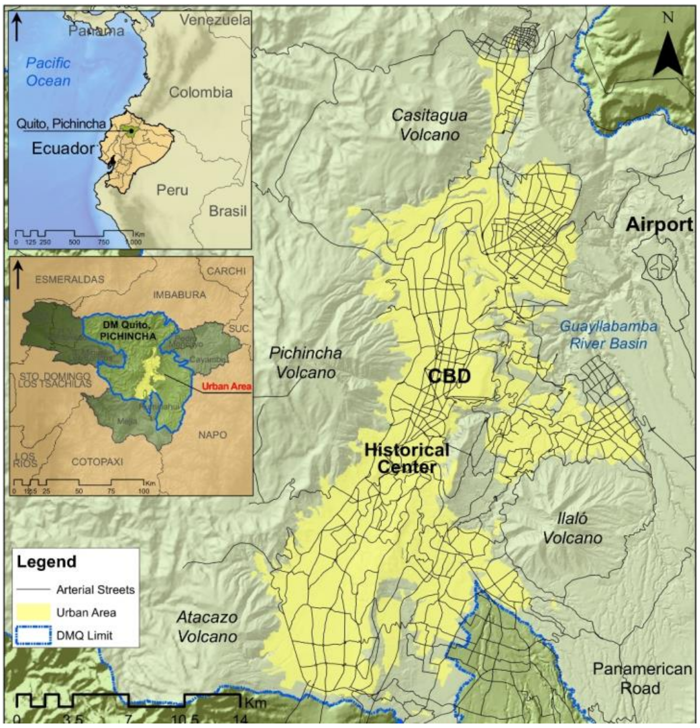

Fig. 2. Location map of Quito. The Urban Area is in yellow; the Central Business District is just near the city's Historic Centre. Source: OpenStreetMap. Processed by ArcMap 10.3.

Quito is a city with a high population and economic density. It is the first Ecuadorian city to sign an agreement with Google to publish mobility information using the Google Maps platform. Quito encourages local and international citizens to use this innovative application to get around the city (Gobierno Abierto, 2021). In addition, Google Maps is a platform that can estimate places that people may have visited and routes they may have taken based on their GLH when activated (Google, 2021b).

In mid-March 2020, unprecedented lockdowns were undertaken in Ecuador and other Latin-American countries because of the rapid spread of the COVID-19 outbreak. The government imposed different restrictions to reduce mobility and slow down the spread of the infectious disease in the country. Similar to Oxford COVID-19 Government Response Tracker (OxCGRT), which highlights patterns in the timing of policy adoption and subsequent relaxation and re-imposition and illustrates how behavioural and epidemiological indicators can change (Hale et al., 2021), in our study, four restriction levels were identified, in Line with Benítez et al. (2020): Level 0 indicates no restrictions (before COVID-19). Level 1 indicates restrictions for indoor places and crowded public events and ensures compliance with distancing protocols. Additionally, the progressive plan of return to work/studies. Level 2 indicates moderate restrictions like the schools and universities closing (online classes), teleworking for public and private companies, declaration of the state of exception during nights and/or weekends and commerce restricting occupancy to 50%. Level 3 indicates total lockdown, with restrictions like national quarantine, national curfew in the afternoon/night, all borders closing, suspension of regular work days for the public and private sector, and limit for circulation of private vehicles based on the number of license plate (only two days a week), suspension of international flights, quarantine days for foreign travellers (humanitarian flights), prohibition of mass gatherings and only medical, police and military staff can circulate (Fig. 3)

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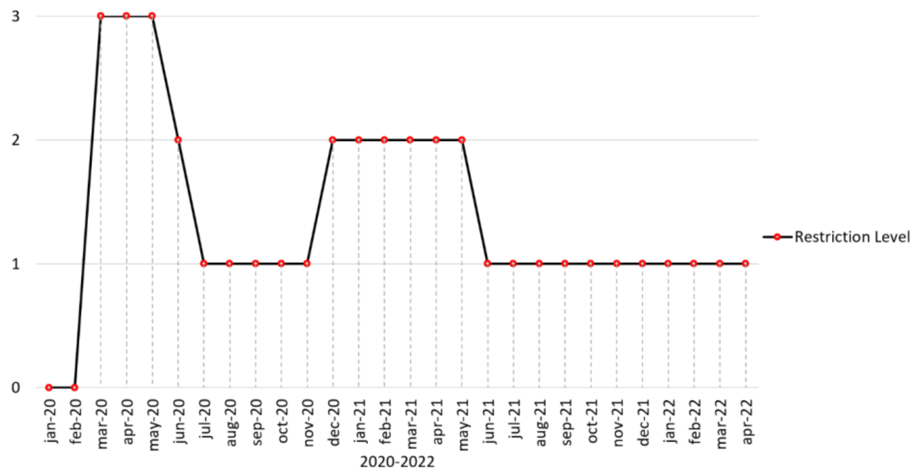

Fig. 3. Restriction levels in Quito over 2020-2022 period. The restriction levels are: 0 (No restrictions), 1 (Light restrictions), 2 (Moderate restrictions) and 3 (Full restrictions).

In April 2022, health authorities of Quito recorded 298,385 confirmed cases (49.58% men, 64.46% between 20 and 49 years old) and 3,614 deaths (Secretaría Metropolitana de Salud, 2021).

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Data framework

The data framework includes GLH and socio-demographic data of participants. For GLH data, by mid-2021, we organised an information session at the university to inform details of the project and explain how we would use it and the treatment we would give to the data. All participants were motivated to invite family members or friends to the study. Participants were recruited voluntarily, and only adults (age 18+) participated. There are many benefits of using longitudinal GLH data for HAS analyses. The amount of data depends on when participants activate the GLH option in their Google Account and whether the mobile device has the 'location history reporting' option turned on. All participants were briefed on how to verify/activate the GLH option. When they did so, they agreed to participate in the study. As Google generates the GLH data, researchers did not intervene in generating the GLH data, only in requesting the file from the participants. After receiving the file, a recruitment questionnaire to collect socio-demographic information was applied. All data was stored under strict ethical and privacy terms.

The objective of our research is to investigate how COVID-19 restrictions influence HAS. Since the focus is to determine how large the weekly HAS is, participants who do not have PRE and POST-COVID data are excluded from the analysis. Additionally, we consider only weeks with at least 5 days of data for the weekly HAS analysis.

After all exclusions, 263 participants met the requirements for this research. Fig. 4 shows how the number of participants with GLH data is distributed over time and the amount of data collected by year. Note that participants do not necessarily have data throughout the entire analysis period. Whether the participant has PRE and POST COVID data is the only requirement, and as mentioned, it depends on when the participant activated the GLH option.

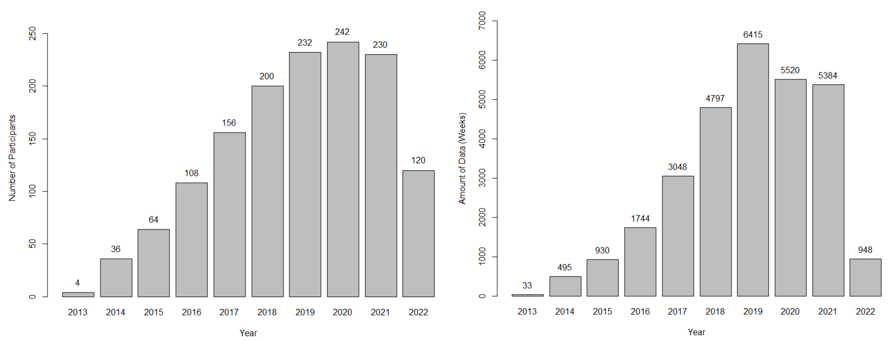

Fig. 4. Number of participants with GLH data and the amount of data collected over the 2013-2022 period. The number of participants increases every year, considering Google started with the GLH option in 2009. The amount of data decreases during the pandemic.

The data framework development includes three successive stages involving three different environments: Data collection (Google) (Page & Brin, n.d.), APL generation (Python) (van Rossum, 1991), and HAS computation for multilevel modelling (R) (Team R Core, 2018). Fig. 5 shows a schematic overview of the data Framework.

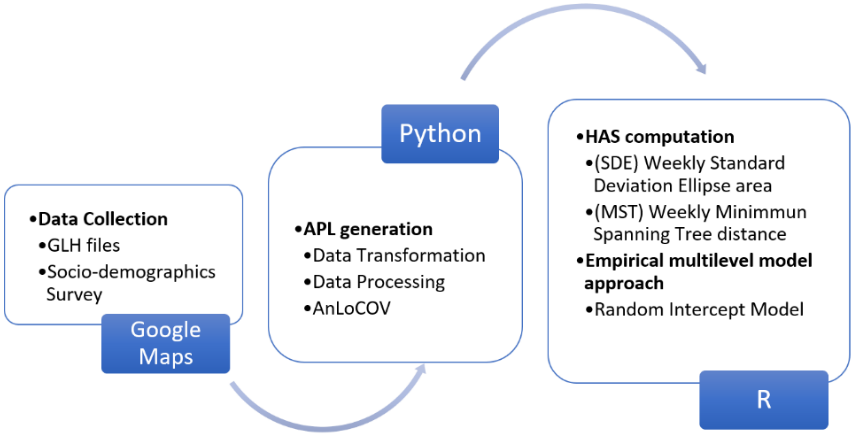

Fig. 5. Schematic overview of the data framework. Each environment is in a blue box.

Data Collection

Data were collected by using the Google Maps Platform (Google, 2021a). Participants who met the requirements for this research downloaded their GLH JSON data files from Google and sent them to us for further analysis. Each participant was also asked to give socio-demographic information by answering an online survey via Google Forms (Google, n.d.) and providing informed consent to use and share their GLH data. We provide a brief statistical description of the socio-demographics in Table 1.

Categorical Variable	Percentage
University Staff – Yes (No)	50.19% (49.81%)
Workers – Yes (No)	39.92% (60.08%)
Live in your own home – Yes (No)	69.96% (30.04%)
Access to a private car – Yes (No)	47.15% (52.85%)
Dependent children (U12) – Yes (No)	39.16% (60.84%)
Gender – Male (Female)	56.65% (43.35%)
Usual transportation pattern – Public transport (Car)	68.44% (31.56%)
Incomes	
Low income	68.82%
Medium income	28.52%
High income	2.66%
Home location	
North of Quito	38.02%
Centre of Quito	6.46%
South of Quito	32.32%
Valleys of Quito	18.25%
Out of Quito	4.94%

Table 1a. Socio-demographic information of participants (Categorical Variables). (N=263).

Numerical Variable	Mean (SD)	Minimum	Maximum
Age	26.66 (8.5)	18.00	64.00
Number of household members	4.63 (1.99)	1.00	18.00

Table 1b. Socio-demographic information of participants (Numerical Variables). (N=263).

APL Generation

This stage computes weekly APLs from GLH data. Overall, four steps are required for APL generation:

- First, a transformation from the JSON flat files to a CSV file organised in the form of a matrix.
- Second, a data cleaning step with filtering and compression according to the distance between consecutive GPS points. The filtering process deletes GPS points considered as noise or outliers in the trajectory. For example, when the calculated speed between two consecutive GPS points is higher than 200km/h, the second GPS point is considered an outlier and is subsequently removed from the dataset. The compression step further reduces the number of GPS points while preserving the trajectory properties. For example, when the Euclidean radius distance between consecutive GPS points is less than 50 m, it implies the points are in a very close neighbourhood of the same location. Subsequently, all these points are merged into a single point whose location is given by the median of all point coordinates, while the associated timestamp corresponds to the first point.
- Third, a weekly trajectory trips classification. All consecutive GPS points with a minimum length of 200 m are converted into weekly trajectories. These weekly trajectories are split into trips with a minimum gap threshold of 30 min and a minimum length of 100 m.
- Finally, the weekly APL identification within each trajectory trip. When the person stays at least 5 min within a Euclidean radius distance from a given GPS point location during the trip, it forms an APL. The APL's time is the time of the initial GPS point, and the coordinates are the median latitude and longitude values of all the GPS points found within a radius distance of 1 Km. Our methodology also ranks all APLs and labels each one based on a minimum radius proximity of 50 m and the number of visits to similar locations at different times. Density-based spatial clustering analysis is conducted by using the DBSCAN algorithm. Each cluster is sequentially labelled, starting from 0, whereas cluster 0 corresponds to the most visited APL over time.

Fig. 6 shows a summary of the workflow. It is important to note that the APL Generation process includes two levels of data anonymisation (the first based on gravity and the second based on density), which guarantees participants’ privacy (Moncayo-Unda et al., 2022). The full description, including algorithms for APL generation and the anonymised dataset, is publicly available on GitHub (Moncayo-Unda, 2021a) and Mendeley Data (Moncayo Unda et al., 2022) respectively.

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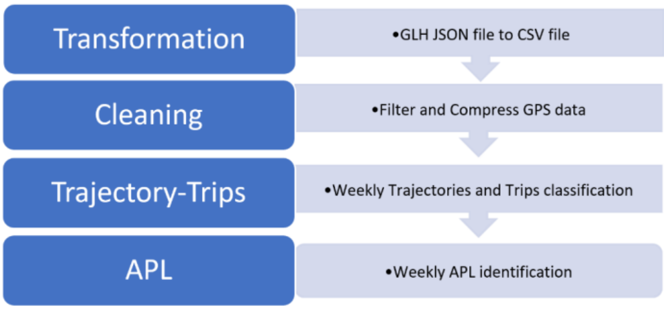

Fig. 6. Generic workflow of APL generation. Each step is in the blue boxes. A brief description in the light blue boxes.

Fig. 7 illustrates APL generation steps. As shown in Fig. 7 (c), many GPS points are removed, and the dataset keeps only APLs for the participant.

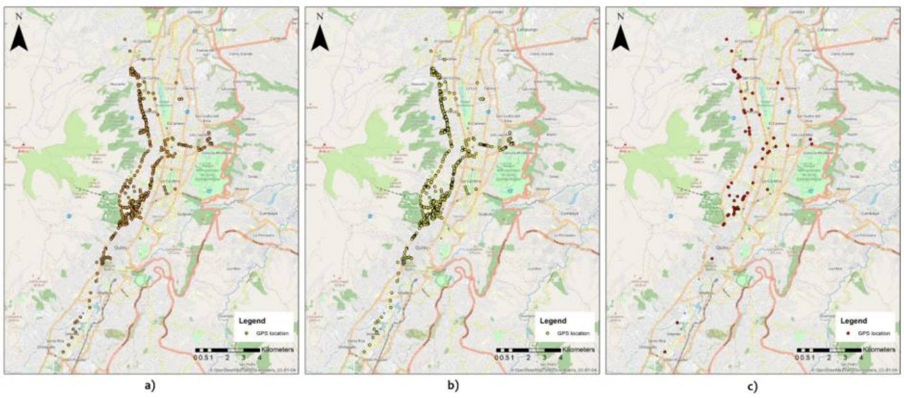

Fig. 7. Sample APL weekly generation process for one person. (a) Data before processing. (b) Data after filtering and compression. (c) APL identification. Source: OpenStreetMap for the base map and GPS location points by the authors. Processed by ArcMap 10.3.

HAS computation

The HAS computation stage requires the development of suitable measures to operationalise the HAS size concept. We develop two indicators, one to understand the weekly spatial behaviour size (Standard Deviation Ellipses) and the other to measure the weekly extent of travel patterns (Minimum Spanning Trees).

The Standard Deviation Ellipse (SDE) arises as one of the classical statistical measures for representing the dispersion of a set of GPS points around its centre. It is typically employed to draw the points' geographical distribution trend by summarising both dispersion and orientation (Wang et al., 2015). It has been concurrently developed in several research domains, such as biological habitat research, transportation research and human geography. The standard deviational ellipse is determined based on the assumption that the locations follow a bivariate normal distribution. This distribution can be centred around a central location determined as the arithmetic mean of the unique coordinates or the weighted average by the frequency of visits at some locations (Y.-C. Chen & Dobra, 2020). The major axis of the ellipse is the regression line of the latitude on the longitude coordinates. Thus, the orientation of the ellipse reflects the sign of the correlation between coordinates (Sherman et al., 2005). In this paper, we characterise the dispersion around the weekly APLs along two orthogonal axes by the SDE area calculation, which gives an idea of the weekly HAS size. The function computes the SDE from a set of weekly APL points, captures the directional bias of the spatial point pattern and orients the ellipse in the direction of maximum dispersion. The mean centre is calculated based on the longitude and latitude coordinates of the APL points. Fig. 8 illustrates different SDE representations.

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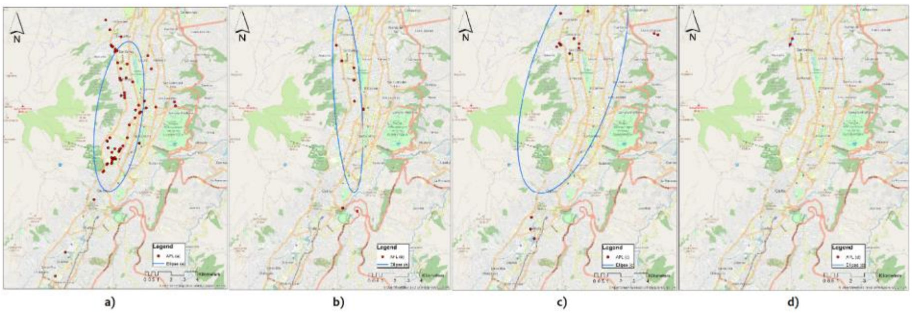

Fig. 8. Sample Standard Deviation Ellipse (SDE). Red points represent the one-week APL data of a study participant. a) No restrictions (before COVID-19), b) Light restrictions, c) Moderate restrictions, d) Full restrictions. Source: OpenStreetMap for the base map and GPS location points by the authors. Processed by ArcMap 10.3.

The Minimum Spanning Tree (MST) employs a more realistic representation of human travel. As opposed to the SDE approach, which employs only the locations, the MST is constructed with respect to a road network that spans the reference area and also considers the order in which the locations were visited (origin-destination trip). An individual's activity spaces are represented by the spanning tree that covers the part of the network defined by the union of the shortest road network paths that connect consecutive visited locations (Y.-C. Chen & Dobra, 2020). The spanning tree is usually measured using its length. Another approach is using the total area of buffers with a fixed length around the road network segments. These buffers attempt to capture the space around the road network segments that might be known to an individual by walking around (Kim & Ulfarsson, 2015). The MST disadvantage is the dependency on the availability of road network data, such data might not have been collected at all or have lower quality in rural areas or in low-resource countries. Moreover, if the APLs are recorded at larger time intervals, approximating the route followed by an individual by the shortest path between two consecutive road locations might be imprecise. For this reason, in this paper, we use the graph theory approach, in which the MST is a subset of the edges of a connected and edge-weighted graph that connects all the vertices without any cycles and with the minimum possible total edge weight. A particular case used in a wide range of fields is a Euclidean Minimum Spanning Tree (EMST). It is a spanning tree of a graph with edge weights corresponding to the Euclidean distance between vertices represented as points in the plane (or space) (March et al., 2010). In our case, the size calculation of the HAS using MST does not account for the paths chosen by the participants; only the Euclidean distance between APLs is considered as the edges of the network to represent an approximation of the spatial extension (because of applying Boruvka's algorithm). The shortest distance a participant needs to join all their APL represents the weekly HAS distance. The function computes the EMST from a set of weekly APL points using the dual-tree Boruvka algorithm. Fig. 9 illustrates different MST representations.

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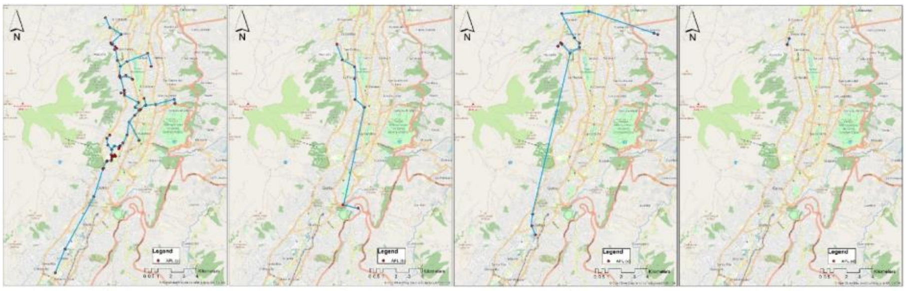

a) b) c) d)

Fig. 9. Sample Minimum Spanning Tree (MST). Red points represent the one-week APL data of a study participant. a) No restrictions (before COVID-19), b) Light restrictions, c) Moderate restrictions, d) Full restrictions. Source: OpenStreetMap for the base map and GPS location points by the authors. Processed by ArcMap 10.3.

We base our developments on Algorithms for HAS computation developed in the R software environment (Team R Core, 2018). Our code is available publicly on a GitHub repository (Moncayo-

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Unda, 2021b). Note that the SDE area and MST distance calculation aggregates all APLs, so no privacy-sensitive information is retained for the empirical modelling. However, explicit approval from the university's ethical committee was requested. For a graphical illustration of the APL generation process and HAS computation, a randomly selected participant's APLs, SDE and MST are visualised using the original set of GPS coordinates.

Empirical multilevel model approach

The study of human behaviour generally involves repeated longitudinal observations of participants of the same population, ordered in time and space. Two sources of variability appeared on these repeated measures: the variability between the observations measured on the same participant (within-person variability) and between the participants. One often needs to analyse data with nested sources of variability: pupils in classes, company employees, periodically repeated measurements in participants, etc. It is usually important to take into account the variability associated with each level of nesting.

A multilevel mixed-effects model is an advanced statistical approach that highlights the relationship between these two types of variations. Mixed-effect models incorporate both fixed and random effects. Fixed effects are parameters associated with an entire population or with certain repeatable levels of experimental factors. On the other hand, random effects are associated with personal experimental units randomly extracted from a population (Pinheiro & Bates, 2006). These models can specify and estimate the relationship between response (dependent) variables at different levels of hierarchical structures (individual, groups, sub-groups; Goldstein, 2011).

Hierarchical models can analyse how a covariate measured at different levels of a hierarchical structure can influence the response variable by permitting the group characteristics at the higher levels to be involved in modelling the individual outcomes. This procedure is performed by partitioning the total variance of the outcome into within-cluster and between-cluster components. Hierarchical models allow intercepts (Random Intercept Model), slopes (Random Slope Model), or both intercept and slopes (Random Intercept and Slope Model) to vary between groups at higher levels (Khoda Bakhshi & Ahmed, 2021).

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This study followed the Random Intercept Model with two levels. Level 1 is the smallest unit (the week), whereas Level 2 denotes the cluster of units (the participant). The main idea is to examine the variance of the Level 1 outcome as a function of predictors on Levels 1 and 2 (M. Cools & Moons, 2016). The model is expressed as follows:

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$$Y_{ij} = \beta_{0j} + \beta X + \mu_{0j} + \epsilon_{ij}; i = 1, \ldots., n; j = 1, \ldots., m$$

where:

n is the number of weeks,

m is the number of participants,

Y_{ij} is the outcome variable for the i^{th} week and participant j,

β_{0j} is the fixed intercept for participant j,

β is the vector of regression coefficients,

X is the vector of explanatory variables,

μ_{0j} is the random effect accounting for the variation of fixed intercept for participant j, and

ϵ_{ij} is the residual.

Variable definitions

Since the focus of this work is to determine how much area (SDE) and extension (MST) people cover weekly, weeks with less than five days of data are excluded from the analysis. After this selection, 263 participants and 29314 weeks have data with the indicated number of days.

Dependent variables

The weekly HAS measures, the Standard Deviation Ellipse area (expressed in km^2), and the Minimum Spanning Tree distance (expressed in km) define the dependent variables in the models. Table 2 presents descriptive statistics for the dependent variables.

Dependent Variable (name)	**Mean**	**Standard Deviation (SD)**
Standard Deviation Ellipse Area **(SDE)**	39.06 km^2	52.75 km^2
Minimum Spanning Tree Distance **(MST)**	27.47 Km	21.89 km

Table 2. Mean and standard deviation of the dependent variables (n=29314, m=263). Variable names are given within parentheses.

Independent variables

The restriction levels due to COVID-19 and socio-demographics are the independent variables. Further details and basic statistics can be found in Table 3.

Independent Variable	**Description / Values**	**Area SDE (km^2)**		**Distance MST (Km)**		**Freq (%)**
		Mean	**SD**	**Mean**	**SD**	
Categorical Variables						
Restriction levels	0 - No restrictions	40.59	52.07	28.66	20.73	63.55
	1 - Light restrictions	40.20	55.69	27.85	24.25	21.09
	2 - Moderate restrictions	35.04	54.05	24.28	23.04	11.49
	3 - Full restrictions	19.74	36.40	15.43	18.44	3.87
University member	No	49.35	62.14	32.14	24.10	52.61

	Yes	27.65	36.54	22.29	17.75	47.39
Working status	No	32.15	45.61	23.69	19.35	57.55
	Yes	48.44	59.84	32.59	23.99	42.45
Home type	Leased	33.46	46.31	26.04	23.10	26.93
	Own	41.13	54.78	28.00	21.40	73.07
Owner of a vehicle	No	30.38	42.77	22.47	18.62	49.91
	Yes	47.72	59.85	32.45	23.69	50.09
Children under 12 years in the household	No	38.14	52.97	26.34	21.11	63.11
	Yes	40.65	52.32	29.40	23.04	36.89
Gender of participant	Female	35.22	46.17	24.88	17.82	40.2
	Male	41.65	56.60	29.21	24.08	59.8
Usual transport pattern	Car	52.94	62.21	35.2	25.54	34.51
	Public Transportation & Others	31.75	45.32	23.4	18.43	65.49
Household monthly income	High	68.40	74.26	33.41	24.55	3.09
	Low	35.72	50.54	26.54	22.09	65.95
	Medium	43.25	53.56	28.87	21.00	30.96
Home location	Centre	21.83	27.32	21.75	16.72	7.17
	North	42.44	50.99	28.77	21.04	38.75
	Out of Quito	71.23	91.22	32.92	27.50	5.20
	South	25.34	37.62	24.85	22.36	31.53
	Valley	53.92	61.93	30.07	21.83	17.36
Numerical Variables						
Age of participant	(mean = 27.46; SD = 8.57; min. = 18; max. = 64)					
Number of persons in the household	(mean = 4.53; SD = 1.94; min. = 1; max. = 18)					

Table 3. Descriptive statistics of the independent variables (n=29314, m=263).

Results and analysis

According to the longitudinal perspective, the study analyses 29314 weeks with at least five days of data distributed among 263 participants in 10 years (2013 to 2022). On average, per participant, 112 weeks of data were available, ranging from a minimum of 2 weeks to a maximum of 364 weeks. About one-third of the weeks (36.45%) concerned post-COVID-19 weeks.

For the multilevel approach, the linear mixed-effects model identifies the HAS variability as a function of the restriction levels due to COVID-19 plus socio-demographics as fixed effects and a random intercept for participants as a random effect. Residuals did not reveal any apparent deviations from homoscedasticity or normality; p-values were obtained by likelihood ratio tests. Intrapersonal correlation is assessed by computing intraclass correlation (denoted as ICC hereafter) using the "ICC" package (Wolak, 2015). This intraclass correlation indicates what portion of the total variance occurs between persons and indicates how similar observations of the same respondent are. A value of ICC=0.38 for the SDE area and ICC=0.46 for the MST distance supports the use of the random intercept model in this paper, whereas a classical general linear model would violate the assumption of independence of the error terms. The ICC for the SDE area is slightly lower than the one of MST distance, indicating that different MSTs for the same person are more similar in comparison to the SDEs and as such, the SDE area seems to capture the intra-person variability of the HAS more efficiently. For a person, the HAS for one week could be similar to another one. This is not a classic linear regression model, the observations are not independent, and it is important to use the appropriate technique to account for this existing dependency.

The following formulas define the basic and full model for the dependent variable SDE area:

$$SDE \sim 1 + (1|idParticipant)$$

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$$SDE \sim rLev + uMem + gender + hLoc + vOwn + uTPatt + hType + wStat + chU12$$
$$+ incomes + age + hSize + (1|idParticipant)$$

The following formulas define the basic and full model for the dependent variable MST distance:

$$MST \sim 1 + (1|idParticipant)$$

$$MST \sim rLev + uMem + gender + hLoc + vOwn + uTPatt + hType + wStat + chU12$$
$$+ incomes + age + hSize + (1|idParticipant)$$

In all cases $(1|idParticipant)$ is used to denote the random effect for each participant on the model.

We used the "lme4" package (Bates et al., 2015) to compute the models. Each dependent variable was analysed separately. Table 4 shows the estimates and p-values for the full models.

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Variable	**Description / Values**	**Area SDE**		**Distance MST**	
		Estimate	**p**	**Estimate**	**p**
Restriction levels	1 – Light	-0.43	0.518	-2.03	**<0.001** ***
	2 – Moderate	-5.33	**<0.001** ***	-5.49	**<0.001** ***
	3 – Full	-17.26	**<0.001** ***	-12.62	**<0.001** ***
University member	Yes	-6.36	0.100	-1.53	0.385
Gender of participant	Male	3.62	0.274	2.89	0.057
Home location	North	12.76	0.066	4.07	0.199
	Out of Quito	31.15	**0.002** **	6.71	0.132
	South	0.58	0.934	1.59	0.621
	Valley	18.23	**0.015** *	2.80	0.410
Owner of a vehicle	Yes	5.01	0.261	2.47	0.224
Usual transport pattern	PT & Others	-5.87	0.222	-5.25	**0.017** *
Home type	Own	6.22	0.086	2.45	0.138

Working status	Yes	5.47	0.186	3.98	**0.035** *
Children under 12 years in the household	Yes	3.05	0.394	4.56	**0.005** **
Household monthly income	Low	-10.41	0.318	-1.05	0.825
	Medium	-5.39	0.610	0.06	0.991
Age of participant	--	0.38	0.096	0.23	**0.029** *
Number of persons in the household	---	-0.48	0.588	-0.86	**0.035** *

Table 4. Random intercept model results for Standard Deviation Ellipse (SDE) and Minimum Spanning Tree (MST). p-value significance codes: <0.001 == (***), [0.001;0.01] == (**),]0.01;0.05] == (*), >0.05 == None

In the table, significant p-values are in bold. Based on this statistical analysis, we can draw some interesting conclusions.

Moderate and full levels of restrictions decrease the HAS area of the participants, while home location increases it mainly when people live far from the central business district of Quito. On the other hand, for the HAS extension, socio-demographic factors are more influential. As expected, levels of restrictions also decrease the HAS extension. Additionally, socio-demographic factors such as the use of public transportation and others, the working people, the existence of children under 12, the age, and the number of people living in the household significantly influence the variability of the HAS extension, increasing or decreasing it depending on the sign of the estimate.

The ANOVA between the base and the full models indicates that the levels of restriction due to the lockdown and socio-demographics significantly affect the HAS area (SDE) $X^2(18) = 280.02, p = 2.2e^{-16}, \propto < 0.001$; and the HAS extension (MST) $X^2(18) = 899.72, p = 2.2e^{-16}, \propto < 0.001$.

Finally, the maximum variance inflation factor (VIF) among the different explanatory variables was 1.94, indicating that multicollinearity did not significantly affect the results (James et al., 2017).

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Discussion and Conclusions

The HAS is constrained by the needs and desires of the person and his household. Mobility restrictions due to lockdown levels because of the COVID-19 pandemic also influence these constraints. The HAS variability implies how the person's APLs vary between weeks, determined by their travel routines. The HAS area and extension have been examined in this study to reveal the HAS variability with the GPS records contained in the GLH data.

Using the Standard Deviation Ellipse to represent the HAS area and the Minimum Spanning Tree for the HAS extension, the statistical analyses in this study have examined the weekly longitudinal variations considering the restriction levels due to the COVID-19 pandemic plus the socio-demographic characteristics of the participants. An individual-specific error component is introduced in the model to account for unobserved heterogeneity, that is, differences across persons that do not change over time and are not explained by the explanatory variables in the model. That is why the study successfully demonstrates how each variable influences the HAS size and extension by applying a mixed-effects model.

The statistical analyses reveal that weekly HAS area measurements are more dispersed than those of the HAS extension. As expected, the restriction levels significantly influence the variability of both the HAS areas and HAS extensions, causing them to decrease considerably in a range varying from 5.33 km^2 to 17.26 km^2 for the HAS area and from 5.49 km to 12.62 km for the HAS extension. Our findings clearly show that when light measures are imposed, there is no effect on the area of the HAS, but there is a significant effect on the distance travelled with 2.03 km of reduction. The restriction levels can be systematised due to their similarity across different geographical regions, ensuring the reusability of our methodology.

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Socio-demographic factors are more influential on the HAS extension than on the HAS area. Home location significantly influences the variability of HAS area, increasing it by 31.15 km^2 when people live out of Quito. Other factors influencing the variability of HAS extension are childcare (increasing by 4.56 km), use of public transportation (decreasing by 5.25 km), being employed (increasing by 3.98 km), age (increasing by 0.23 km), and household size (decreasing by 0.86 km). Both the number of significant variables and the intra-cluster correlation are smaller in the case of SDE, suggesting that SDE captures better variations that cannot be attributed to socio-demographics.

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We compute these statistical results based on data from participants who have enabled Location History for their Google accounts. The data represents a sample that may or may not represent the exact behaviour of a wide population. A convenience sample primarily composed of the University staff members was used for this study, balancing richness versus selectivity for the long-term data. This selectivity is an important factor for COVID travel changes as university staff may be informed differently from the full population. Increasing the participant sample becomes essential for generalising the findings in future research. However, privacy is the main problem when researching location data. The data anonymisation process is fundamental to motivate people to participate in this kind of study and, consequently, increase the sample data to understand better the HAS variability and to share with the research community for future studies.

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At the local level, there is no related work on HAS variability analysis. Developing countries often address urban planning issues using old census data and do not consider the real spatial dimensions of people's mobility. The information provided by Google enriches this kind of study. Quito is one of the countries that report mobility data to Google, making it a helpful mobility tool. It is essential to include other data sources, like the COVID-19 Community Mobility Report, which provides movement trends across categories such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. This report gives a real calculated variation of some activity spaces within cities.

By showing that the HAS size varies from week to week and from participant to participant, this study has shed new light on the HAS size variability from a weekly and longitudinal perspective. The empirical findings of this study add to the body of knowledge on HAS variability. At the same time, there are some practical applications in transportation planning, for example, in analysing traffic and access to crowded places under lockdown constraints or assessing possibilities for mobility modification in response to policy measures.

The results show that the interventions had, by far, the strongest effect on HAS. In this context, it is necessary to strategically locate essential services and ensure that amenities are close to residential areas to improve urban resilience in case of future pandemics. As people continue to work remotely and interact virtually, the demand for certain types of travel may decrease, influencing how planners allocate resources for different transport modes.

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Furthermore, our findings show that the restrictions imposed by lockdowns and social distancing measures have disproportionately affected individuals who rely on public transport. In this context, the concept of HAS intersects with social justice and equity issues. Limited access to transport options and essential services can increase social exclusion and negatively impact vulnerable populations. Transport planners must address these disparities by considering not only the physical accessibility of activity spaces but also the availability of safe and reliable transport options during challenging times like the pandemic.

Policymakers could use this study to make informed decisions in planning public policies related to mobility and transportation that adapt to the pandemic situation and the population’s needs, accelerating the shift to sustainable urban mobility practices, such as micro-mobility and active transport. The study, however, is subjected to several limitations, as discussed in the above paragraphs. Addressing these limitations remains a future research topic.

Ethics statements

All data has been anonymised to respect the privacy of participants. Informed consent was obtained from each one by completing the demographic data survey. In addition, because we used data from Google, the Board for Ethics and Scientific Integrity of the University confirmed that the project meets the standard ethical requirements and complies with the GDPR.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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