



Space–time accessibility supports participation in after-work leisure activities

Yuan Liao ^{a,b},*, Rafael H.M. Pereira ^c, Jorge Gil ^d, Silvia De Sojo Caso ^b,
Laura Alessandretti ^b

^a Department of Human Geography, Lund University, Lund, Sweden

^b Department of Applied Mathematics and Computer Science, Technical University of Denmark, Denmark

^c Institute for Applied Economic Research (Ipea) - Brazil, Data Science Division, Brazil

^d Department of Architecture and Civil Engineering, Chalmers University of Technology, Gothenburg, Sweden

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ABSTRACT

Understanding how accessibility shapes participation in leisure activities is central to promoting inclusive and vibrant urban life. Conventional accessibility measures often focus on potential access from fixed home locations, overlooking the constraints and opportunities embedded in daily routines. In this study, we apply a space–time accessibility (STA) metric rooted in the capability approach, capturing feasible leisure opportunities between home and work given a certain time budget, individual transport modes, and urban infrastructure. Using high-resolution GPS data from 2415 working residents in the Paris region, we assess how STA influences leisure participation during weekdays, measured as the diversity of leisure locations visited and activity duration. Observed destination choices confirm that most individuals select leisure locations within their STA-defined opportunity sets, validating the metric as a proxy for capability sets. Structural equation modeling shows that STA exerts a significant positive total effect on leisure participation ($\beta = 0.14$, $p < .001$), driven by a significant direct effect ($\beta = 0.18$, $p < .001$) that is only modestly offset by an indirect pathway through reduced travel time ($\beta = -0.04$, $p < .01$). Individual attributes also directly shape participation: active mode use and higher education promote leisure engagement, while local poverty and caregiving responsibilities constrain it. These findings highlight the value of person-centered, capability-informed accessibility metrics for understanding inequalities in urban mobility and informing transport planning strategies that expand real freedoms to participate in social life across diverse population groups.

1. Introduction

Transport accessibility is central to inclusive cities through its influence on individual mobility and activity participation (Allen and Farber, 2020; Luz et al., 2022; Liao et al., 2025). By shaping how easily people can reach different locations and activities, spatial accessibility defines the scope of places and social environments individuals can access (Pereira et al., 2017), particularly activities taking place in third places, that is, informal settings outside home and work (e.g., cafés, community centers, parks) that foster meaningful social interactions (Oldenburg and Brissett, 1982). When transport opportunities are limited, the risk of social exclusion rises for certain groups (Luz and Portugal, 2022; Gallego Méndez et al., 2023). Studies have shown that greater proximity to certain destinations is associated with higher participation rates in those activities (e.g., Reimers et al., 2014). Yet,

it remains unclear whether access to transportation is effectively associated with more participation in third-place activities, and how individual capabilities and time constraints shape this relationship.

Although third-place activities are crucial for social inclusion and well-being, they have received less scholarly attention than commuting and essential travel domains in accessibility literature (Luz et al., 2022; Tomasiello and Giannotti, 2023). Visits to third places affect individuals' social exposure by linking them to wider society beyond institutional settings (Oldenburg and Brissett, 1982). Such exposure often depends on people's flexibility in allocating time to discretionary activities—that is, non-obligatory activities such as socializing, leisure, or informal errands that they choose to engage in. Recent studies reflect the growing attention to third-place activities in accessibility research, e.g., evaluating inequalities in access to destinations like parks (Tomasiello and Giannotti, 2023; Barboza et al., 2024). Among

* Corresponding author at: Department of Human Geography, Lund University, Lund, Sweden.
E-mail address: yuan.liao@keg.lu.se (Y. Liao).

the third-place activities, this paper focuses specifically on leisure activities. This choice highlights that transport systems must accommodate the diverse and time-sensitive mobility demands associated with activities that improve individuals' well-being (Lee, 2022).

Accessibility to leisure opportunities is shaped by transport systems, which play a key role in enabling activity participation, yet it is usually examined in a static manner (Luz and Portugal, 2022). Home- or work-based accessibility measures, typically operationalized through network-based models of potential access (Levinson and King, 2020), estimate how many leisure destinations can be reached within a given travel-time threshold. Most studies in the literature utilize such home-based and static measures of transport accessibility (Ryan et al., 2023). There are two major limitations of static measures. First, this stream largely overlooks trip chaining and trips that originate from non-home locations, particularly workplaces. Many leisure activities, central to urban vibrancy and the fostering of social interactions (Botta and Gutiérrez-Roig, 2021), take place after work rather than from home (McGuckin and Murakami, 1999; Farber et al., 2013; Barboza et al., 2024). Second, static approaches neglect the dynamics of individuals being in motion throughout their daily activities. One of the key factors shaping individuals' ability to engage in leisure activities is their travel time budget, defined as the amount of time people are willing to spend traveling each day. Individuals who pursue a wider range of activities—particularly discretionary ones, such as leisure, social engagements, or personal errands—tend to accumulate longer daily travel time budgets, as these additional and geographically dispersed activities extend the time spent traveling (Joly and Vincent-Geslin, 2016). Conversely, individuals with tighter activity schedules or fewer discretionary commitments exhibit more limited daily travel-time budgets and remain anchored to a narrower set of proximate destinations. Activity locations in proximity reduce the required travel effort for reaching comparable opportunities, thereby lowering the effective time budget needed to satisfy activity demand (Chen and Yeh, 2021).

Unlike home- or work-based measures, space–time accessibility metrics account for the spatio-temporal constraints of an individual's space–time prism (Kim and Kwan, 2003; Victoriano et al., 2020; Saraiva and Barros, 2022), offering a more realistic proxy for their ability to access leisure opportunities. However, space–time accessibility metrics are data-intensive and vary substantially across individuals, requiring detailed information to compute, including home and work locations (Saraiva and Barros, 2022). The resulting measures also require careful interpretation, as understanding them often depends on additional personal attributes to disentangle the complex factors shaping accessibility outcomes (Chen and Yeh, 2021). Consequently, applying these metrics—and studying their downstream effects on activity participation—generally requires high-resolution datasets, such as the one used in the present study.

To date, our understanding of how transport accessibility shapes leisure activity participation remains largely static. This study draws on a unique geolocation dataset capturing multi-day movement trajectories for over 2000 residents of the Greater Paris region, alongside detailed socio-demographic and household information. In this study, we (i) quantify individual space–time accessibility to leisure opportunities, (ii) examine its explanatory power for total travel time and leisure activity participation (location diversity and activity duration), and (iii) assess how individual and household attributes shape these relationships.

The remainder of this manuscript is organized as follows. The introduction continues with a brief review of related work (Section 1.1), followed by an explanation of the applied conceptual framework (Section 2). We then describe the materials (Section 3) and methodology (Section 4), followed by Section 5, which presents the results and accompanying discussion. The paper concludes with a summary of the main findings in the Conclusion section.

1.1. Related work

Third-place activities play a central role in urban life, yet their use and relevance are strongly structured by individuals' home and work places and personal circumstances. Third-place activities—such as gyms, cafés, and parks—significantly shape social interactions, identity, and community connectedness (Oldenburg and Brissett, 1982; Farber et al., 2013). For example, some third places, such as shopping centers, strategically located to connect diverse neighborhoods, could attract visitors across socioeconomic groups and foster inter-group exposure (Nilforoshan et al., 2023). Institutional locations, i.e., homes and workplaces, serve as anchors that structure daily mobility patterns, constraining the accessibility and relevance of third places (Miller, 1991). The effect of these anchors on mobility is intertwined with individual attributes, lifestyle, and activity demand (Luz and Portugal, 2022; Barboza et al., 2024).

Leisure activities, which typically happen in third places, differ behaviorally from the mandatory activities that anchor daily schedules. In activity-based frameworks, home and work function as fixed anchors: spatially and temporally rigid commitments around which the rest of the daily program is organized (Schwanen et al., 2008). Leisure activities, by contrast, are characterized by high scheduling flexibility, spatial substitutability, and optionality: they can be more easily relocated, rescheduled, shortened, or dropped altogether when time pressure mounts (Ettema et al., 2007; Schwanen et al., 2008). These properties mean that leisure participation is especially sensitive to residual time budgets, the discretionary time that remains after mandatory commitments and commuting have been satisfied (Kitamura, 1984; Joly and Vincent-Geslin, 2016). Unlike commuting trips, where the destination is fixed and the decision reduces to route and mode, leisure trips involve simultaneous choices of whether, when, where, and for how long to participate, making them inherently more responsive to variations in accessibility (Ettema et al., 2007).

A growing body of evidence indicates a strong correlation between transportation accessibility and physical activity participation. Higher accessibility levels are strongly correlated with participation in total, mandatory, and discretionary activities (Fransen et al., 2018; Luz et al., 2022). Proximity to walkable areas promotes higher levels of physical activity (Althoff et al., 2025). Improving accessibility in neighborhoods with concentrations of low-income or carless households located outside major transit corridors has also been shown to increase daily activity participation (Allen and Farber, 2020). The behavioral distinctiveness of leisure from mandatory activities makes leisure a revealing lens for evaluating how well transport systems convert potential access into actual participation: rigid activities will be undertaken regardless of accessibility conditions, whereas flexible activities amplify the signal of accessibility differences across individuals and places. Indeed, studies have found that enhancing public transit accessibility can particularly benefit participation in discretionary activities among disadvantaged groups (e.g., Zhang et al., 2022).

Nevertheless, most existing studies rely on home-based cumulative opportunity (Allen and Farber, 2020; Luz et al., 2022) or simple proximity measures (McCormack and Shiell, 2011) of accessibility, treating individual attributes separately. This approach is essentially static and overlooks the mechanisms through which accessibility shapes mobility. For example, while greater job accessibility may be associated with higher leisure participation at the aggregate level (Luz et al., 2022), such a misalignment between the activity types used to measure accessibility and those used to measure participation obscures policy relevance and undermines individual-level insights.

In contrast, space–time accessibility is a person-based approach that enables the examination of intra-group and intra-location heterogeneities, thereby offering a deeper understanding of accessibility inequalities across individuals (Neutens et al., 2010; Saraiva and Barros, 2022). It builds on two core concepts: an individual's trajectory in space and time (space–time path), and the set of potential trajectories

an individual could take given temporal and spatial constraints (anchors) (Kwan, 1998). They define the geographical extent of accessible opportunities (space–time prisms). Measures of space–time accessibility range from direct depictions of prisms (Miller, 1991) to empirically scalable methods based on travel time budgets (Saraiva and Barros, 2022). Recent advances in space–time accessibility account for the feasibility of chaining activities between home and work, given an individual's travel time budget, residential and workplace locations, and the built environment (Saraiva and Barros, 2022; Barboza et al., 2024). This formulation reflects realistic mobility patterns, such as engaging in leisure activities on the way home from work, and thus provides a useful proxy for assessing both mobility efficiency and opportunities for third-place participation.

To disentangle the complex pathways through which space–time accessibility shapes leisure participation, we employ Structural Equation Modeling (SEM), a widely used approach in travel behavior research (Golob, 2003; Kroesen and Van Wee, 2022; Song et al., 2016). SEM is particularly adept at dissecting intricate causal structures (Golob, 2003; Kroesen and Van Wee, 2022). For instance, SEM has been applied to explore the interdependencies among land use, socio-demographic attributes, and travel patterns (Song et al., 2016), and to model mediating variables such as car ownership when analyzing the built environment's influence on travel behavior (Zhang et al., 2025). This method has been shown to provide valuable insights into how built environment characteristics—including density, diversity, connectivity, and accessibility—affect various outcomes, such as individual transport emissions, health outcomes, and rural income, by shaping residents' travel choices and capabilities (Azmoodeh et al., 2023; Kroesen and Van Wee, 2022; Li et al., 2024; Song et al., 2016).

2. Conceptual framework

In this study, we operationalize the notion of accessibility as a human capability using the space–time accessibility (STA) framework (Pereira et al., 2017; Luz and Portugal, 2022). In this approach, individuals' time budgets and mobility resources (e.g., main transport mode, amenity distribution) interact to shape the opportunity sets that one can reach, including third-place activities such as leisure (Fig. 1). First, individuals' conversion functions, shaped by personal attributes and constraints such as household responsibilities, education, and mobility skills, determine the inputs to the capability set. Specifically, sociodemographic characteristics shape the two building blocks of space–time accessibility: residential and workplace locations (space–time anchors) and the main transport mode (the mobility resource). The spatial–temporal dimension of capability — that is, the leisure opportunities reachable within a given time budget, mode, and set of anchors — thus emerges from these conversion processes. Together, the conversion function and resources (transport systems, amenity distributions) produce the capability set: the set of leisure destinations one could feasibly visit on a given trip chain. Second, this potential is realized through actual travel decisions, in which activity demand and time allocation jointly determine which opportunities are pursued. Third, mobility enables participation in activities at the destinations reached. This resource → potential → realization → participation logic motivates treating the capability set and mobility as distinct constructs: the capability set captures what is spatially and temporally feasible, while mobility captures the behavioral process through which feasible opportunities are selectively converted into actual engagement.

A key insight here is that these two processes (accessibility and mobility) can have opposing effects on leisure diversity. A larger capability set expands options (positive effect), but individuals in high-accessibility settings may also travel less (because nearby opportunities suffice), and lower travel time is associated with lower diversity. This countervailing mechanism, which we demonstrate empirically through SEM decomposition, is the core advancement over (Luz and Portugal, 2022), who examined the link between mobility, activity participation,

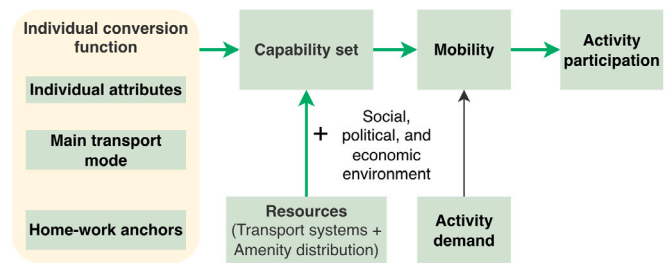


Fig. 1. Accessibility as a human capability. Conceptual framework illustrating how we conceptualize space–time accessibility (STA) as a human capability, adapted from Luz and Portugal (2022), Luz et al. (2022). The diagram shows how factors influencing activity participation interact with capability sets. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and wellbeing without quantitatively disentangling the mediating role of travel behavior. Compared to Luz and Portugal (2022), which treats achieved functionings as a single construct encompassing both travel behavior and activity participation, we decompose this stage into two distinct components: mobility (realized travel) and activity participation (Fig. 1). This decomposition allows us to model mobility as a mediating mechanism through which the capability set is selectively converted into actual leisure engagement, enabling identification of both direct and indirect pathways from accessibility to participation.

Transport planning approaches that equate accessibility solely with the provision of infrastructure or services often overlook these individual-level conversion processes, which are shaped by personal characteristics, environmental barriers, and cultural norms (Pereira et al., 2017; van Eldijk et al., 2022; Luz and Portugal, 2022). This capability-oriented framework thus shifts attention to how varying levels of space–time accessibility are necessary to ensure equal opportunities, social inclusion, and the freedom to engage in third-place activities essential for well-being and development.

The flexibility and substitutability of leisure activities have direct implications for how we operationalize STA. Because leisure destinations can be swapped, rescheduled, or foregone entirely, the relevant capability set is not a single location but a field of opportunities within an individual's space–time prism. Someone with many reachable options can substitute one destination for another under time pressure; someone with a narrow set faces a binding constraint that may suppress participation altogether. Moreover, because leisure occupies the residual time window after mandatory commitments, the STA value determines not only where individuals can go but whether they participate at all, making leisure activities relatively sensitive to variations in space–time resources.

In this study, we hypothesize that the factors shaping an individual's participation in leisure activities are the individual conversion function, the capability set, and the mobility, indicated by the thick green arrows in Fig. 1. The list of all opportunities accessible by a person (their *capability set*) is operationalized from two building blocks: individuals' home and work/study locations, and their transport and amenity resources.

3. Materials

This study draws on a combination of large-scale mobility traces, contextual geographic data, and socio-economic information to characterize individuals' opportunities and participation in activities in the Greater Paris region (Section 3.1). We integrate high-resolution GPS travel diaries from the 2023 Enquête Mobilité par GPS (EMG) (Section 3.2) with detailed attributes on household and personal characteristics (Section 3.3), public transport and road network infrastructure (Section 3.4), and point-of-interest (POI) distributions (Section 3.5). Together, these materials provide a comprehensive foundation for quantifying space–time accessibility and examining the determinants of



Fig. 2. The Paris region and its public transit lines. Gray lines represent IRIS boundaries, and black lines depict roads and motorways. The right panel provides a zoomed-in view of central Paris, where green points mark home and work locations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

leisure and third-place activity participation across diverse population groups.

3.1. Study area: The Paris region

The Paris region, commonly known as the Île-de-France, is the most populous of France's eighteen regions, with an estimated 12.27 million residents as of January 2023 (INSEE, 2022). Centered on the capital Paris in the north-central part of the country, it covers 12,012 km², about 2% of metropolitan France, yet accounts for nearly 20% of the national population. In the Paris region, population density reaches about 20,200 inhabitants/km² in the city of Paris, decreases to around 7000 inhabitants/km² in the inner suburbs, and averages roughly 3700 inhabitants/km² across the wider conurbation (La Grande Conversation, 2023).

The Paris region (see Fig. 2), with its monocentric urbanization pattern, has one of the world's densest and most multifaceted transport networks—spanning multiple transit modes and innovative services (metro, RER, tramways, buses, and on-demand services), coordinated by Île-de-France Mobilités (IDFM). The region also offers robust ecosystem support via Mobility-as-a-Service (MaaS) platforms, integrating public transit with shared mobility, MaaS apps, and seamless ticketing (Île-de-France Mobilités, 2023). Residents frequently take multi-modal trips and exhibit rich variation in their mobility patterns across individuals (Yin and Leurent, 2023).

3.2. Trip records

We use a dataset collected via the Enquête Mobilité par GPS (EMG 2023) initiative and made available through participating in the Net-Mob 2025 Data Challenge (Chasse et al., 2025). The EMG 2023 survey, conducted between October 2022 and May 2023, covered 3337 residents aged 16–80 in the Paris region, excluded non-residents, tourists, and the immobile, and used a multichannel recruitment strategy combining quotas and random draws to ensure representativeness (Chasse et al., 2025).

In this study, we analyze 14,169 individual-day records from 2415 individuals with identified home and work locations, including information on date, day type (e.g., strike, holiday), origin, destination, transport mode, trip duration, and purpose. Origins and destinations

are represented by the centroids of the visited locations' corresponding H3 hexagons at resolution 10 (Uber Technologies, Inc, 2018), each covering approximately 0.015 km².

Participants were observed for a median of 5 weekdays per individual (mean = 4.4, range 1–6). The analysis was restricted to weekday observations (Monday–Friday), comprising 78.7% of all recorded trips. Although the raw data flagged atypical day types (public holidays, school holidays, bridge days, and strike days), we retained all weekday observations because the survey-provided day weights adjust for representativeness across day types and because trips on such atypical days accounted for only 1.3% of individual-weekday records. Individual-level variables were aggregated from daily records using weighted medians for individual metrics.

3.3. Socio-economic attributes

The data from the EMG 2023 survey provides a rich set of sociodemographic, household, and mobility-related attributes. It includes basic identifiers and residence information such as municipality codes, as well as demographic variables like sex, age, education level, and socio-professional category. We also augment the attributes with the poverty rate at the IRIS (9-digit) zone level, used as a proxy for income in 2021. This measure corresponds to the share of individuals living in households whose standard of living—after accounting for taxes, transfers, and social benefits—falls below 60% of the national median disposable income (Institut national de la statistique et des études économiques (INSEE), 2024). Household composition is captured through the number of persons and their age distribution, as well as the type of housing. Mobility resources and constraints are represented by indicators of driving licence ownership and car availability, complemented by information on access to two-wheelers, bicycles, e-scooters, and other mobility devices. The dataset also records subscriptions to public transport and other mobility services, alongside a statistical weighting coefficient for representativeness.

We focus on the main attributes: age, gender, poverty rate (zone level), education, household structure, main transport mode, active mode use, and public transport subscription. Among these attributes, household structure captures gradations in domestic responsibility that shape time availability for leisure. Single parents bear sole caregiving burden, representing the most constrained category. Couples with

children share significant obligations, typically involving escort trips and coordinated schedules. By contrast, individuals living alone or in couples without children face minimal domestic care demands. Those living with parents—often younger adults—may benefit from shared household tasks, partially offsetting their own time constraints.

3.4. Public transit and road network data

For public transit, we collected GTFS schedules from transport.data.gouv.fr, the French national open data platform for mobility, which provides official timetables and service information across transit operators (IDFM, accessed on 30 June 2025). Road network data were obtained from OpenStreetMap, an open, collaboratively maintained geospatial database offering detailed and regularly updated representations of streets, pathways, and transport infrastructure (accessed on 1 July 2025).

3.5. Point of interest (POI) data

POI data were collected via the Overture API, restricted to the geographical extent of the trip records, and filtered for a confidence level above 0.7 ([Overture Maps Foundation, 2023](https://overturemaps.com/)). We then extracted POIs and their primary and secondary labels that are aligned with the activity purposes recorded in the trip data, *Social & Leisure* (67k), consolidated through a combination of GPT-4o-assisted classification (Essential needs, Health services, Education, Civic and utility, Social & Leisure, and Other) and manual validation.

4. Methodology

In this section, we outline the key components of the four methods used in our analysis. We begin by describing the calculation of space-time accessibility (Section 4.1), followed by the approaches used to assess how well individuals' capability sets (reflected in their space-time accessibility) align with their observed spatial choices of leisure destinations (Section 4.2). We then present the methods for quantifying mobility individually through total travel time and individual participation in third-place activities (Section 4.3). Finally, we introduce the structural equation model and its specification to disentangle the complex relationship between space-time accessibility and leisure activity participation (Section 4.4).

4.1. Space-time accessibility

In this study, we operationalize individual-based capability set as *space-time accessibility* (STA). Specifically, we focus on the *cardinal accessibility* dimension, which accounts for the number of opportunities (leisure POIs, including parks, etc.) that individuals can feasibly reach within their available time budget ([Saraiva and Barros, 2022](#)). In other words, it counts the number of opportunities located within a person's Potential Path Area (PPA), which is the geographical area a person can reach given her space-time constraints ([Saraiva and Barros, 2022](#)) (see Fig. 3).

The measure builds on the space-time feasibility concept ([Kwan, 1999](#)) and is modified based on the cardinal individual-based accessibility measure proposed in [Saraiva and Barros \(2022\)](#). Each individual is assumed to have a fixed total travel time budget t_i^b and use their revealed main transport mode (car or public transport). An activity destination k is considered accessible to individual i if the time required to visit k does not exceed the individual's time budget. In other words, the total time required to (i) travel from home to work ($t_{hw,i}$), (ii) travel from work to k ($t_{wk,i}$), and (iii) return from k to home ($t_{kh,i}$) does not exceed the time budget, as if as if the individual makes a single leisure



Fig. 3. Space-Time Accessibility (STA). The light-green region represents the Potential Path Area (PPA), i.e., all locations reachable given the individual's time budget and travel constraints between home and work. Opportunities within this area (dark green) are accessible, while those outside it (light green) are not. The direct home-work path is shown in bold orange, and a feasible work-activity-home path is shown in blue. This illustrates the STA of an individual, defined as the set of feasible opportunities that fall within the individual's PPA. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Source: Adapted from [Saraiva and Barros \(2022\)](#).

stop on the trip from work to home, as more commonly found in the population ([McGuckin and Murakami, 1999](#)).

$$a_i^k = \begin{cases} 1, & \text{if } t_{hw,i} + t_{wk,i} + t_{kh,i} \leq t_i^b \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where:

- $t_{hw,i}$ is the travel time from home to work,
- $t_{wk,i}$ is the travel time from work to activity location k ,
- $t_{kh,i}$ is the travel time from activity location k to home,
- t_i^b is the travel time budget of individual i .

With the overall space-time accessibility (STA_i , the capability set), the number of opportunities within STA_i is A_i for individual i , given by the sum of all feasible opportunities within a given category:

$$A_i = \sum_{k \in \mathcal{L}} a_i^k \quad (2)$$

where $\mathcal{L}$ denotes the set of all candidate leisure POIs in the study area.

By construction, STA is mechanically determined by three inputs: the geolocations of home and work anchors, the travel speed of the main transport mode, and the time budget. Variation across individuals thus arises not from the formula—which is identical for all—but from variation in these inputs, which are themselves socially structured: residential and workplace locations reflect housing markets and employment access; mode choice is shaped by income, household composition, and local infrastructure; and time budget is largely affected by the conjunction of activity responsibilities. STA captures the spatial-temporal opportunity space that emerges from these socially determined conditions, consistent with the capability approach, in which conversion factors shape the resources that produce capabilities rather than entering the capability metric directly.

In this study, we set each individual's travel time budget t_i^b to 90 min, based on the empirical median of 82 min observed in our

dataset. This threshold is consistent with the well-established travel time budget regularity i.e., that daily travel time budgets tend to cluster around 60–90 min across diverse urban settings, suggesting a stable behavioral constant in human mobility (Marchetti, 1994; Schafer and Victor, 2000). The fixed time budget is an intentional design choice rather than a limitation: adopting person-specific budgets derived from observed travel times would introduce circularity, as the explanatory variable would then be partly determined by the behavioral outcome it is meant to predict. Commuting time (t_{hw}), travel time from home to work, is empirically estimated using the weighted median of observed commuting trips. Discretionary activity k is defined as a visit to leisure-related locations (e.g., bars).

For calculating t_{wk} and t_{kh} , we fix the departure time at 17:00, which resembles the work-to-home trip chaining scenario with an added leisure activity stop on the way from work to home. Travel times between home, work, and candidate leisure POIs were computed for both public transit and car, using GTFS schedules and road network data, implemented through the r5r package (Pereira et al., 2021). We also conduct and report sensitivity analysis with alternative budgets (i.e., 60, 75, 90, and 120 min) for both car and public transit and alternative departure times (i.e., 16:00, 17:00, and 18:00) for public transit.

Due to the presence of zero values and the right-skewed distribution of raw accessibility counts, we apply the inverse hyperbolic sine (IHS) transformation:

$$A_i^* = \sinh^{-1}(A_i) = \ln \left(A_i + \sqrt{A_i^2 + 1} \right) \quad (3)$$

where A_i is the raw count of accessible leisure POIs for individual i , and A_i^* is the transformed value used in the downstream analysis. The IHS transformation behaves similarly to the natural logarithm for large values, but is defined at zero ($\sinh^{-1}(0) = 0$), which preserves the zero-accessibility cases while reducing the influence of extreme values.

Because the STA framework requires both a home and a work anchor to define the space-time prism, our analysis is restricted to those for whom both locations could be identified, effectively limiting the sample to the working population and excluding non-workers, retirees, and unemployed individuals whose accessibility constraints may differ substantially.

4.2. Capability set vs. spatial choices

To gain a finer-grained understanding of how accessibility shapes behavior, we assess whether individuals tend to select activity locations that align with what their modeled opportunity landscape (STA) predicts as desirable, or whether actual behavior departs from this logic.

This behavioral analysis focuses on the alignment between the ranked set of feasible locations STA_i (adding up to A_i) within individuals' potential path area and the locations they actually visited. By comparing observed choices against random draws from STA_i , we test for selectivity—that is, whether individuals systematically prefer most accessible locations (see Fig. 4).

We evaluate whether individuals tend to visit the activities that are the most accessible (e.g., those that take a shorter time to reach) using a ranked comparison: For each individual i , we operationalize their STA_i as a ranked list of feasible locations (H3 hexagons at resolution 8, $\sim 0.74 \text{ km}^2$). We focus on H3 hexagons rather than raw GPS coordinates for two reasons. First, not all locations labeled as leisure in the GPS data correspond to entries in the leisure POI dataset extracted from Overture Maps. Second, the GPS coordinates have been preprocessed by the data provider to H3 level-10 centroids as a privacy measure, making precise point-level POI matching infeasible. Consequently, POI assignment must rely on an appropriate spatial unit rather than exact-coordinate matching. These spatial units (H3 hexagons at resolution 8) are further sorted from 1 (best = most accessible, lowest travel time increase) to N_i (worst = least accessible, highest travel time increase).

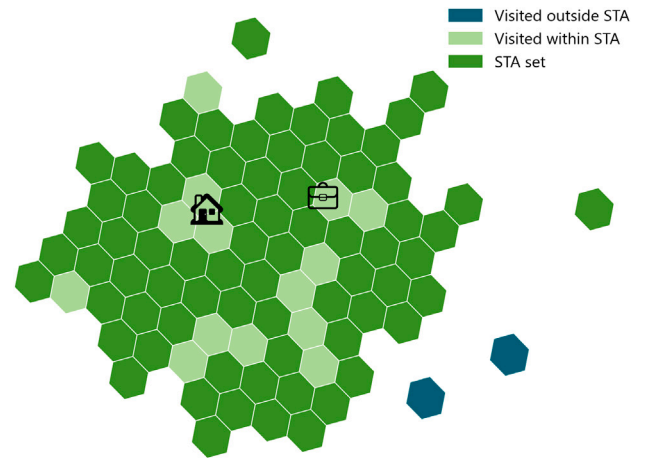


Fig. 4. Space-Time Accessibility (STA) set vs. visited leisure locations. One example individual. Home and work icons show where the person lives and works. Hexagons are at resolution 8, $\sim 0.74 \text{ km}^2$.

We then compare the set of visited locations V_i to this ranking. First, we calculate the share of locations in V_i that fall outside STA_i . Second, we define the test statistic as the average rank of the visited locations falling within STA_i :

$$T_{\text{mean},i} = \frac{1}{K_i} \sum_{\ell \in V_i} \text{rank}(\ell) \quad (4)$$

where $K_i = |V_i|$.

To generate a null distribution, we perform $B = 1000$ random draws of K_i locations from STA_i , computing $T_{\text{mean},i}^{(b)}$ for each. We then derive both the empirical p -value:

$$p_i = \frac{1 + \# \left\{ b : T_{\text{mean},i}^{(b)} \leq T_{\text{mean},i} \right\}}{B + 1} \quad (5)$$

and the standardized effect size:

$$d_i = \frac{T_{\text{mean},i} - \mu_i^{\text{null}}}{\sigma_i^{\text{null}}} \quad (6)$$

where μ_i^{null} and σ_i^{null} are the mean and standard deviation of the null distribution. Negative values of d_i indicate better-than-random performance—i.e., that the individual tends to visit higher-ranked locations than would be expected under random choice.

4.3. Weekday mobility and activity participation

We consider total travel time for mobility quantification. For activity participation, we consider two aspects: (1) the diversity of locations where activities occur (diversity), and (2) the mean leisure activity duration (intensity). Because the travel diary lacks detailed labeling of third-place activities, we approximate third-place participation using all leisure activities ('LEISURE').

We compute the diversity measure based on the distribution of leisure activity locations. For each individual i , we count the number of visits to each distinct leisure location (H3 hexagons at resolution 10) during their data collection period. Let n_i denote the total number of leisure visits, and let K_i^d denote the number of distinct leisure locations visited. Defining $p_{k,i} = n_{k,i}/n_i$ as the relative frequency of visits to leisure location k ($k = 1, \dots, K_i^d$), we compute the Hill number of order $q = 1$, which is given by:

$$H_{1i} = \exp \left(- \sum_{k=1}^{K_i^d} p_{k,i} \ln(p_{k,i}) \right). \quad (7)$$

which reflects the effective number of equally frequent locations visited, and accounts for both richness and evenness in the individual's leisure location distribution.

In operationalizing the quantification of mobility and activity participation, we focus exclusively on leisure activities during weekdays. Since our space–time accessibility measure is built on the home–work–activity–home trip chain, restricting the analysis to regular weekdays ensures consistency between the assumptions underlying the STA metric and the observed travel behavior used to measure mobility and leisure participation. Individual-level indicators (total travel time, leisure location diversity, mean duration of leisure activities) were aggregated across all valid weekday observations for each person.

4.4. Structural equation modeling specification

Based on the data summarized in Table 1, we estimate a structural equation model (SEM) linking (i) individual attributes, (ii) transport mode, (iii) space–time accessibility value A_i^* , (iv) total travel time, and (v) leisure activity participation (latent variable). Let i index individuals. The model variables are:

- i. A_i^* : IHS–transformed space–time accessibility to leisure opportunities;
- ii. Z_i : a vector of exogenous sociodemographic and lifestyle attributes (dummy-coded for household type, gender, education, etc.), retained after preprocessing to remove collinearity and low variance;
- iii. M_i : transport variables, including the main transport mode dummy and the public transport subscription dummy;
- iv. B_i : travel behavior indicator, namely total travel time;
- v. η_i : leisure activity participation, measured by the Hill number of order $q = 1$ (H_{1i}), quantifying the diversity of leisure locations visited, and mean leisure activity duration in minutes (T_i), quantifying the activity intensity.

To avoid imposing causal ordering between two parallel outcomes, we tested whether location diversity and leisure duration could serve as indicators of a latent “leisure participation” construct. The two variables are significantly correlated ($r = 0.31$, $p < .001$), and Bartlett's test confirmed shared variance ($\chi^2 = 208.7$, $p < .001$). Exploratory factor analysis yielded adequate loadings for both indicators ($\lambda = 0.54$), exceeding the 0.4 threshold for meaningful loadings (Hair et al., 2010). The modest shared variance (28.6%) reflects their complementary nature: diversity captures the breadth of leisure engagement across locations, while duration captures depth of time invested. We therefore adopt a latent variable specification in the SEM.

Before estimating the structural equation model, it is important to specify a directed acyclic graph (DAG) that encodes the theoretical and causal assumptions about the relationships among the variables. The DAG serves as a transparent foundation for identifying potential confounding paths, making the assumptions of the model explicit, and ensuring that the SEM structure is both theoretically grounded and empirically justified (Huntington-Klein, 2021). We iteratively evaluated which relationships could be pruned by testing the key conditional independence implications suggested by our theoretical framework. We assessed whether certain connections between variables—such as those linking individual attributes, transport mode, capability set, mobility, and activity participation—could be removed without contradicting the observed data. This process allowed us to identify which dependencies were empirically warranted and which were not, ensuring that the resulting DAG retained only the pathways supported by theory and evidence.

The final directed acyclic graph (DAG) reflects the theoretically informed and empirically tested structure of the relationships among individual attributes, transport mode, capability set, mobility, and activity participation (Fig. 5). Individual characteristics are modeled as

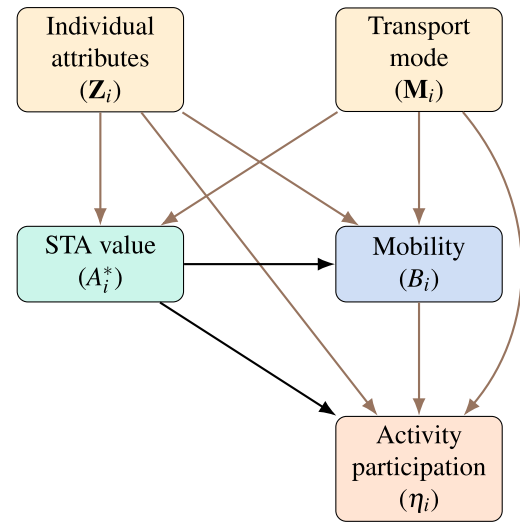


Fig. 5. Pathway structure. This directed acyclic graph shows the hypothesized and empirically validated pathways. Exposure = STA value, Outcome = Activity participation, Black arrows = Hypothesised direct paths, Brown arrows = Biasing paths.

exogenous factors that shape accessibility (capability set), as well as exerting direct influences on trip-making and activity participation. Transport mode variables are also treated as exogenous. Modeling mode choice endogenously led to non-convergence due to identification issues arising from the relationship between binary mode indicators and continuous outcomes. Moreover, mode choice depends on complex factors that are better addressed through dedicated discrete choice models (Ben-Akiva and Lerman, 1985). Our focus is on how transport mode conditions accessibility and leisure participation, not on the determinants of mode choice itself. Therefore, covariances between sociodemographic and transport mode variables are freely estimated, preserving their correlational structure without imposing a causal ordering. The capability set, representing the feasible space–time leisure opportunities available to individuals, is affected by both personal attributes and transport mode, and in turn drives patterns of trip-making and participation. Trip-making operates as an intermediate behavioral mechanism linking accessibility to leisure activity participation. Finally, leisure activity participation is conceptualized as the outcome of multiple interacting pathways: directly from individuals, from transport behavior, and indirectly via both the capability set and trip-making. This structure balances theoretical expectations from time-geography and accessibility theory with empirical evidence from conditional independence testing, ensuring that only statistically supported pathways are retained.

The SEM specifies the relationships in Fig. 5. In the measurement model, the latent leisure participation construct η_i is measured by two observed indicators:

$$H_{1i} = \lambda_1 \eta_i + \varepsilon_{1i}, \quad (8)$$

$$T_i = \lambda_2 \eta_i + \varepsilon_{2i}, \quad (9)$$

where H_{1i} is location diversity, T_i is mean leisure duration, $\lambda_1 = 1$ (fixed for identification), and λ_2 is freely estimated.

The structural model is shown below:

$$A_i^* \sim \alpha_Z^T Z_i + \alpha_M^T M_i, \quad (10)$$

$$B_i \sim a A_i^* + \gamma_Z^T Z_i + \gamma_M^T M_i, \quad (11)$$

$$\eta_i \sim c A_i^* + b B_i + \delta_Z^T Z_i + \delta_M^T M_i, \quad (12)$$

Table 1

Descriptive statistics of the 2415 commuting individuals. Values represent weighted means (continuous variables) and weighted percentages (categorical variables). A_i is transformed using the inverse hyperbolic sine (IHS), while zeros are retained.

Group	Variable	Levels	Mean (SD) or %
Individual attributes	Age	–	43.3 (11.8)
	Poverty rate (IRIS zone level)	–	15.8 (8.3)
	Education	No diploma	1.7
		Vocational	11.7
		Lower secondary	3.0
		Upper secondary	31.4
		3–4-year higher education	15.7
		5-year-and-above higher education	25.6
		Missing	10.9
	Gender	Man	47.6
		Woman	52.4
	Household type	Living alone	12.2
		In a couple w/o children	20.3
		Single parent	11.6
		Living with parent(s)	6.2
		Not related to other household members	1.1
		In a shared apartment	0.3
		In a couple w/ child(ren)	47.2
		Another family member in the household	1.1
	Use of active mode	No	62.1
		Yes	37.9
Space–time accessibility	STA value (>0)	Non-zero Zero	39.7 60.3
	STA value (IHS)	–	3.2 (4.1)
Transport mode	Main transport mode	Car	38.7
		Public transit	61.3
	Public transit subscription	No Yes	35.7 64.3
Mobility	Total travel time (min)	–	96.2 (44.1)
Activity participation	Diversity	–	1.1 (1.4)
	Duration (min)	–	62.5 (99.4)

where A_i^* is space–time accessibility, B_i is total travel time, Z_i is a vector of sociodemographic covariates (gender, education, poverty rate, household type), and M_i is a vector of transport mode variables (public transit mode, PT subscription, active mode).

The total effect of space–time accessibility on each observed indicator is:

$$\text{Total effect on } H_{1i} = (c + a \cdot b) \times \lambda_1, \quad (13)$$

$$\text{Total effect on } T_i = (c + a \cdot b) \times \lambda_2, \quad (14)$$

where c is the direct effect, and $a \cdot b$ is the indirect effect mediated through travel time.

The analysis was performed in R (lavaan 0.6-19) using the diagonally weighted least squares (DWLS) estimator, which is appropriate for models that include categorical or non-normally distributed variables. Continuous variables were standardized to stabilize variances. Weights were normalized to have a mean of one and applied during estimation to account for individual-level representativeness. Multicollinearity was assessed using variance inflation factors (VIF), applying thresholds of 5 (moderate) and 10 (severe). All retained predictors had VIF < 2.2. Education was recoded from 7 levels to a binary (high vs. low/medium) due to high correlation among the category dummies ($r = -0.89$). Household type effects were included only in equations where preliminary estimation indicated statistical significance ($p < 0.05$); non-significant household effects were constrained to zero to improve model parsimony and identification. Rare household categories (<2% of the sample) were excluded. Gender, poverty rate, transport mode, public transit subscription, and active mode use were retained as predictors across all equations. We report standardized coefficients and standard SEM fit indices (CFI, TLI, RMSEA, SRMR). Indirect, direct, and total associations are computed through model-implied parameter combinations.

5. Results and discussion

In this section, we first visualize space–time accessibility and leisure activity participation (Section 5.1). We then report the results assessing the alignment between the modeled capability set and individuals' actual spatial choices of leisure destinations (Section 5.2). Finally, we present the modeling outcomes (Section 5.3), detailing the quantified relationships and how different components link to space–time accessibility and shape leisure participation.

5.1. Space–time accessibility and leisure activity participation

Fig. 6 presents a spatial overview of space–time accessibility value A_i^* and leisure activity participation measures across the study region, highlighting the geographic variations. Fig. 6a shows the proportion of inhabitants with STA > 0, indicating the share of individuals who have feasible opportunities beyond their fixed home and work locations. Higher values are concentrated in the northern central urban areas and scattered across select suburban zones, suggesting greater access to leisure activity opportunities in both dense and well-connected peripheral locations, mainly by car. Activity participation lacks clear spatial patterns (Fig. 6b–c). This suggests that leisure activity participation is more strongly driven by individual-level differences, underscoring the need for appropriate modeling. Sensitivity analyses confirm that STA patterns are robust to variation in both the time budget (60–120 min) and the departure hour (16:00–18:00); details are reported in Appendix (Fig. A.2).

We further visualize how STA relates to leisure activity participation, stratified by main transport mode (car vs. public transit) in Fig. 7.

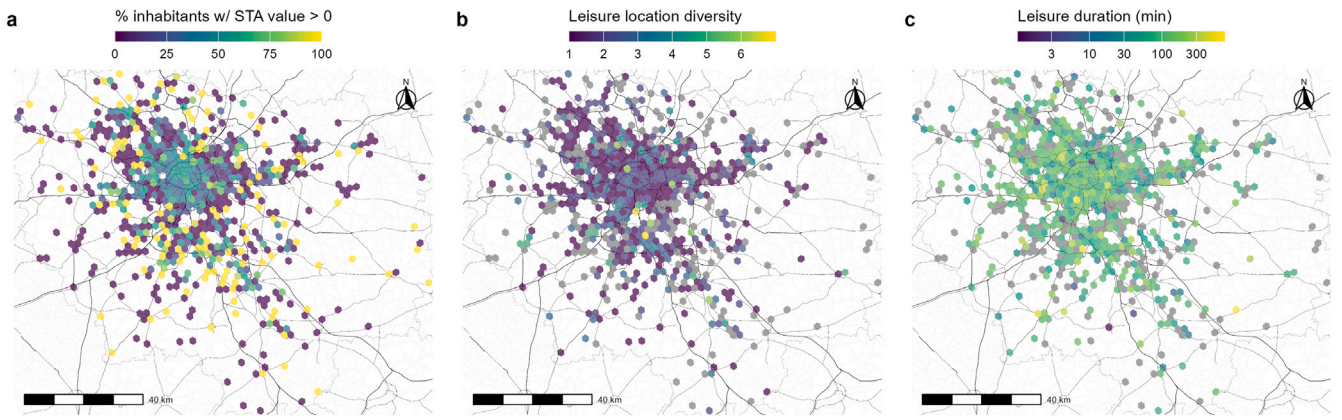


Fig. 6. Space-time accessibility value and leisure activity metrics on the map. a, Share of inhabitants with $A_i^* > 0$. b, Leisure location diversity. c, Leisure activity duration (min), on log-transformed color scale. For b–c, the map shows the weighted median of each zone's inhabitants in the data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

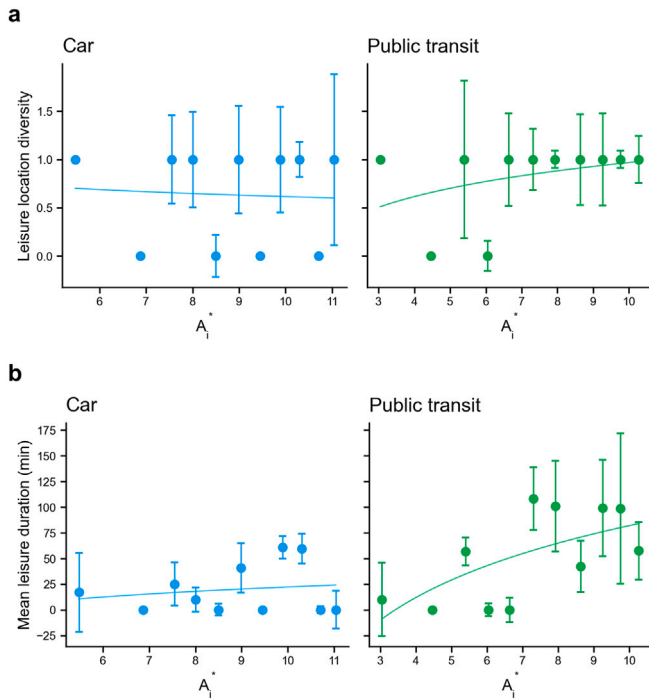


Fig. 7. Space-time accessibility value A_i^* vs. leisure activity participation by mode. a, Leisure location diversity. b, Leisure activity duration (min). Error bars indicate bootstrap median estimation errors.

Leisure location diversity and duration are in general positively associated with STA, especially for public transit users. These visual patterns support our assumptions regarding the interdependence of individual attributes, transport mode choice, and space-time accessibility value (Section 2). SEM outcomes further disentangle their relationships.

5.2. Selectivity in spatial choice of weekday leisure activities

Before examining the structural relationships between STA and leisure participation, we first assess whether the modeled capability sets align with individuals' actual spatial choices, which serves as a necessary validation step to ensure that the STA metric meaningfully captures the opportunity structures it is designed to represent.

Based on 566 individuals with $A_i > 0$ who registered leisure activities during weekdays, we observe a strong alignment between STA_i and actual spatial choices of leisure activities (Fig. 8). The distribution of visited locations outside STA_i is skewed toward lower values (Fig. 8a): the top 20% of individuals make more than half of their visits outside their capability set. Moreover, only 0.2% of individuals have visited zero places within their capability set. Space-time accessibility in this context primarily captures trip-chaining opportunities between home and work, framing leisure visits as secondary or incidental.

Most individuals exhibit negative d_i values (Fig. 8b), indicating a tendency to choose closer locations than expected by chance, as 80% of individuals have significant deviation from being random ($p < 0.05$). This supports the feasibility of using STA as a realistic approximation of individuals' capability sets. A cluster of individuals exhibits strongly negative d_i values with highly significant p -values, while others have values near zero or even positive, suggesting behavior closer to random or worse than random. These results reveal considerable heterogeneity in the degree of behavioral selectivity across the population.

Among all individual attributes considered, only the use of active transport mode shows a statistically significant association with the effect size (d_i), as illustrated in Fig. 8c. Active users exhibit a higher median d_i and a tighter distribution skewed toward weaker selectivity (i.e., more positive values). Individuals who use active modes exhibit significantly higher d_i than non-active travelers, with an estimated increase of 1.04 units ($p < .001$), suggested by the linear regression test $d_i \sim C(\text{Using Active Mode})$. These results suggest that individuals using active mode tend to align less closely with their STA-based opportunity rankings.

Taken together, individuals exhibit varying degrees of alignment with modeled opportunity structures. Active transport users show weaker within-STA selectivity. These findings underscore the value of decomposing the behavioral mechanisms underlying accessibility: individuals do not uniformly act upon modeled opportunities, and their selectivity depends critically on their lifestyle and spatial constraints.

5.3. Modeling outcomes

Having established that individuals' leisure choices align with their modeled capability sets, we now examine whether the breadth of these sets, i.e., space-time accessibility, predicts the diversity of leisure locations visited.

We apply structural equation modeling techniques with the diagonally weighted least squares (DWLS) estimator on a total of 2415

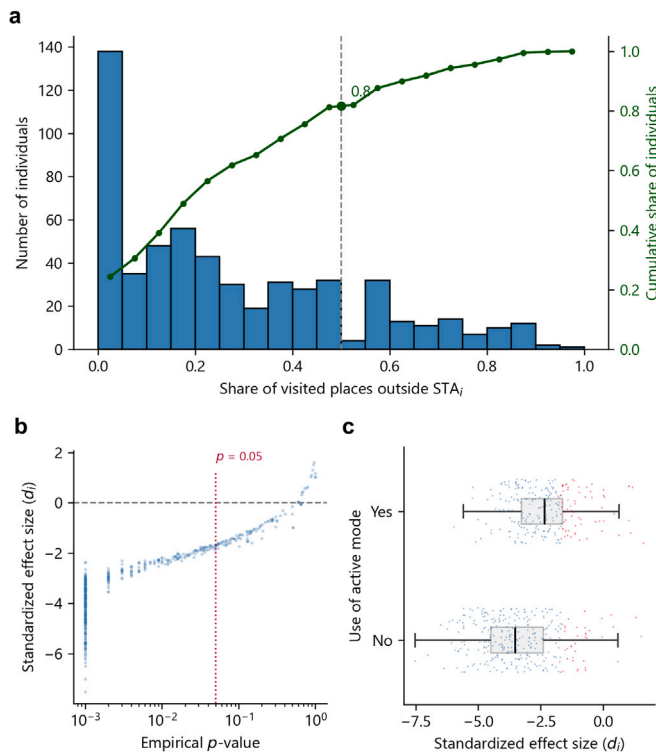


Fig. 8. Selectivity in spatial choice behavior across individuals. a, Distribution of individuals by the share of visited locations outside their modeled feasible set (STA_i), with bar color indicating the proportion of car users in each bin. Bins include lower boundaries. b, Standardized effect size d_i plotted against the empirical p -value from the mean rank test, on a log scale. The vertical line marks the $p = 0.05$ threshold. Each point is an individual. c, Boxplot of d_i stratified by use of active transport mode, with jittered points colored by statistical significance (blue: $p < 0.05$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

weighted observations (individuals) to model leisure activity participation during weekdays. The model demonstrated excellent overall fit, with a Comparative Fit Index (CFI) of 0.987 and Tucker–Lewis Index (TLI) of 0.954. The Root Mean Square Error of Approximation (RMSEA) was 0.029, with a 90% confidence interval of [0.018, 0.041], and the Standardized Root Mean Square Residual (SRMR) was 0.014, all supporting model adequacy (Hu and Bentler, 1999). We assess the robustness of the SEM results to the time budget parameter by estimating the model under restrictive (60 min) and generous (120 min) specifications, fixing departure time at 17:00 given its limited impact (Fig. A.2). Model fit remains good across all specifications, and the pattern of effects are consistent (see Appendix A.2). Therefore, we report the detailed results from the 90-minute specification below.

Significant direct and indirect pathways with standardized coefficients exceeding an absolute value of 0.1 (Fig. 9) highlight the role of household structure, active mode use, and public transport subscription in shaping space–time accessibility, total travel time, and leisure activity outcomes.

5.3.1. Transport mode predicts space–time accessibility

Space–time accessibility is shaped by transport characteristics. Active mode users—those regularly walking or cycling—exhibit significantly higher STA value ($\beta = 0.14$, $p < .001$). Given how STA is evaluated, this could be ascribed to two main mechanisms: (1) these individuals mostly live in the city of Paris, with good proximity to leisure opportunities and good support for walking and cycling; and (2) they have relatively short commuting times (34 min) compared to

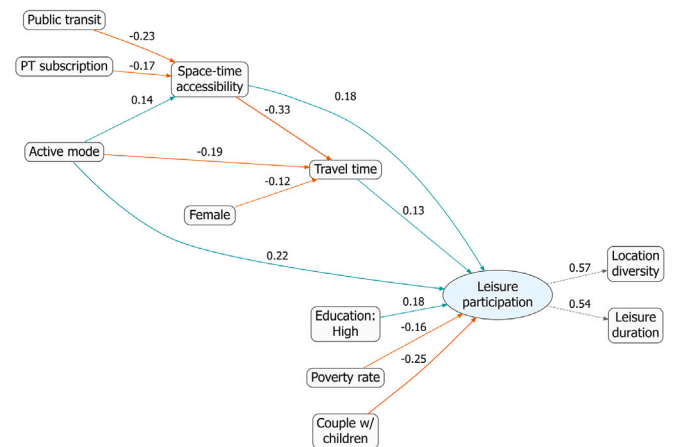


Fig. 9. Structural equation model of factors shaping leisure activity participation. Standardized path coefficients ($p < 0.05$) and $|\beta| > 0.10$ are shown along the arrows, with positive effects in teal and negative effects in orange. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

non-active mode users (43 min), leaving a greater share of the assumed 90-minute budget available for potential leisure activities.

We find that both public transit use ($\beta = -0.23$, $p < .001$) and public transport subscription ($\beta = -0.17$, $p < .001$) are negatively associated with STA. This suggests that, given individuals' fixed daily anchors (home and work/study locations) and their chosen mode of travel, the car provides more effective access to a wider range of leisure opportunities compared to public transport.

Except for the use of active mode, all paths connecting individual attributes to STA are found to be insignificant, with their effects primarily on travel time and leisure participation.

5.3.2. Space–time accessibility predicts travel time together with active mode usage and gender

Space–time accessibility strongly predicts total travel time ($\beta = -0.33$, $p < .001$). Higher STA implies a greater number of accessible leisure opportunities within the space–time prism, which in turn leads to shorter travel times, indicating that part of the activity demand can be met in proximity. The use of active modes is also associated with shorter total travel time ($\beta = -0.19$, $p < .001$), suggesting that those who rely on active transport do so because their activity needs can be met closer to their home and work anchors. Females tend to have shorter travel times compared to males ($\beta = -0.12$, $p < .001$). The total travel time, in turn, serves as a mediator between STA and leisure activity participation.

5.3.3. Leisure activity participation predicted by space–time accessibility, travel time, and individual attributes

Higher accessibility is positively associated with greater leisure participation ($\beta = 0.18$, $p < .001$). This finding underscores a conceptual alignment between space–time accessibility to leisure opportunities and actual participation in diverse leisure locations (0.57) and longer duration (0.54). In other words, individuals with higher accessibility to leisure opportunities are more likely to translate potential into visits to a broader range of leisure locations and longer activities.

Mobility also contributes here: longer travel times increase leisure participation ($\beta = 0.13$, $p < .001$). From the perspective of utility-maximization, longer travel time can still result in higher overall utility if it enables meaningful leisure engagement (De Vos et al., 2016). This effect is around the same magnitude as that of STA directly, underscoring the role of total travel time as a key mediator shaping actual leisure activity participation.

Table 2

Estimation results of SEM (significant at $\alpha = 0.05$). Standardized coefficients reported.

Effect on	Direct	Indirect	Total
Total travel time			
STA value (A_i)	-0.33***	–	-0.33***
Active mode	-0.19***	–	-0.19***
Female	-0.12***	–	-0.12***
Leisure participation			
STA value (A_i)	0.18***	-0.04**	0.14***
Total travel time	0.13***	–	0.13***
Active mode	0.22***	–	0.22***
Education: High	0.18***	–	0.18***
Poverty rate	-0.16***	–	-0.16***
Couple w/ children	-0.25***	–	-0.25***

Notes: STA = space-time accessibility. The indirect effect of STA operates through total travel time. Leisure participation is a latent construct indicated by location diversity and leisure duration. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Active mode use is positively associated with leisure activity participation ($\beta = 0.22$, $p = .001$). Leisure travel is often motivated by social needs, the pursuit of variety, and personal recharge (Stauffacher et al., 2005). Active transport may facilitate these motivations by providing greater flexibility in route selection and opening up opportunities to access varied leisure spaces such as parks, cafés, or community centers. It is plausible that walking or cycling itself becomes part of a user's leisure experience—adding intentionality and value to the travel act.

Individual attributes also shape leisure participation directly. Higher education is positively associated with leisure participation ($\beta = 0.18$, $p < .001$), consistent with evidence that education expands both awareness of and preference for varied leisure opportunities. Conversely, higher local poverty rates ($\beta = -0.16$, $p < .001$) and living in couple-with-children households ($\beta = -0.25$, $p < .001$) are negatively associated with leisure participation, reflecting how economic deprivation and caregiving responsibilities constrain discretionary activity engagement beyond the indirect effects already captured through transport mode and accessibility pathways.

5.3.4. Effect decompositions of space-time accessibility

Decomposition analyses reveal that the space-time accessibility value had both direct and indirect effects on leisure participation (Table 2). The direct effect of accessibility on leisure participation is positive and significant ($\beta = 0.18$, $p < .001$), while the indirect effect through travel time is negative and significant ($\beta = -0.04$, $p < .01$). As a result, the total effect is smaller but remains significant ($\beta = 0.14$, $p < .001$). In addition, active mode use exerted a strong, positive direct effect on leisure participation ($\beta = 0.22$, $p < .001$), underscoring heterogeneity in activity outcomes beyond accessibility constraints.

While the total effect of STA on leisure participation was slightly offset by an indirect effect from shortened travel time, the decomposition highlights that STA does matter: it exerts a positive total effect on both leisure location diversity and activity duration ($\beta = 0.14$, $p < .001$). These countervailing mechanisms suggest that accessibility shapes leisure activity participation in complex ways, rather than through a simple net effect.

6. Conclusions

This study examined the impact of individual-based space-time accessibility (STA) on leisure activity participation, with a focus on the Paris region. By leveraging high-resolution GPS data for 2415 Paris residents, multimodal transport networks, and a capability-based accessibility framework, we demonstrated that STA—operationalized as the feasible set of leisure opportunities within individuals' time budgets—plays a critical role in shaping activity participation.

Our results offer robust empirical evidence that greater transport accessibility promotes more efficient travel (i.e., shorter travel times) to fulfill daily activity demand and supports broader participation in leisure activities (i.e., location diversity and activity duration). Through structural equation modeling, we identified both direct and indirect effects: STA directly promotes greater leisure participation, while it also reduces travel time, which is associated with lower participation. However, the total effect of STA on leisure activity participation is significantly positive. Such countervailing direct and indirect effects (via travel time) demonstrate that expanding opportunity sets does not linearly translate into broader participation, a finding that enriches the theoretical understanding of how capabilities convert into functionalities through the mediating role of mobility behavior. The observed spatial choices of leisure destinations further validated the STA construct as a realistic proxy for individuals' capability sets. This alignment suggests that space-time prisms are not merely geometric constructs but behaviorally meaningful boundaries, providing rare empirical validation of the behavioral relevance of time-geographic constraints for discretionary activities.

Importantly, the study revealed substantial heterogeneity in leisure activity participation across population groups. Education, local poverty, and household composition also directly shape leisure participation: positively for higher education and negatively for local poverty and couple-with-children households. These reflect how human capital, economic deprivation, and caregiving responsibilities influence discretionary activity engagement beyond the indirect pathways through transport mode and accessibility. These findings underscore the importance of considering both the spatial distribution of opportunities and the temporal feasibility of access when designing inclusive transport policies.

There are a few limitations in the present work. First, our framework models accessibility and participation at the individual level and therefore cannot capture the joint, coordinated nature of many leisure activities — such as group outings or shared meals — where participation depends not only on one's own space-time constraints but also on those of companions, meaning that individual-level accessibility may be a necessary but insufficient condition for actual engagement. Second, we acknowledge that the current STA operationalization captures only single-stop work-leisure-home chains on weekdays and does not account for weekend leisure patterns, multi-stop trip chaining, or leisure activities originating directly from home. Third, non-workers are excluded from the analysis, despite potentially facing more severe accessibility constraints due to limited transport resources, reduced temporal flexibility, or geographic isolation from leisure opportunities. Our findings on inclusive mobility, therefore, apply specifically to the commuting population; the mechanisms linking STA to leisure participation may operate differently for individuals whose daily routines are not structured around a work anchor. Extending the STA framework to non-commuting populations would require alternative formulations, such as home-based prisms defined by discretionary time budgets and habitual activity anchors rather than fixed workplaces, representing an important direction for future research.

By embedding accessibility into a human capabilities framework, this work shifts the discourse from infrastructure provision toward understanding how individuals convert transport resources into meaningful participation. Future research should extend this analysis to non-commuting populations, incorporate dynamic time budgets, and examine the longitudinal impacts of accessibility improvements on social inclusion and well-being. As cities pursue more equitable and sustainable mobility systems, more nuanced accessibility metrics, such as space-time accessibility, can serve as valuable tools to identify gaps, monitor policy impacts, and prioritize interventions that expand real freedoms to engage in everyday urban life.

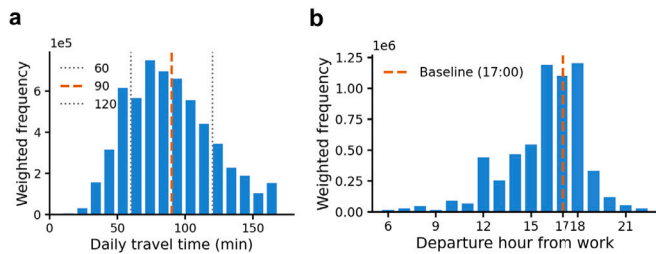


Fig. A.1. Parameter choices of space-time accessibility. a, Distribution of daily travel time. b, Distribution of departure time from work.

CRedit authorship contribution statement

Yuan Liao: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Rafael H.M. Pereira:** Writing – review & editing, Software, Methodology. **Jorge Gil:** Writing – review & editing, Methodology. **Silvia De Sojo Caso:** Writing – review & editing, Methodology. **Laura Alessandretti:** Writing – review & editing, Methodology.

Declaration of competing interest

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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Appendix. Sensitivity test results

A.1. Space-time accessibility distributions

To assess the robustness of STA to its two main parametric assumptions, we conducted sensitivity analyses varying departure time and time budget (Fig. A.1).

First, varying the time budget from 60 to 120 min at a fixed 17:00 departure, the share of individuals with STA > 0 increases from 28.7% to 59.7% for car users and from 13.1% to 49.4% for public transit users. The baseline of 90 min, approximating the empirical median of observed daily travel times (82 min), thus produces intermediate coverage rather than ceiling or floor effects. Second, varying the departure hour from 16:00 to 18:00 for public transit users at a fixed 90-minute budget, both the mean number of accessible opportunities (979–1029) and the share with non-zero STA (32%) remains stable, indicating that the measure reflects underlying spatial structure rather than schedule-specific artifacts. Together, these results confirm that while absolute STA magnitudes scale with the time budget as expected, the qualitative patterns are robust to reasonable parameter variation.

A.2. SEM outcomes

To assess the robustness of our findings to the operationalization of space-time accessibility, we conducted sensitivity analyses varying the travel time budget parameter. Given the limited impact of departure time (16:00–18:00, see Fig. A.2), we re-estimated the full SEM specification under two alternative scenarios fixing departure time as 17:00 in the baseline: a restrictive 60-minute budget representing

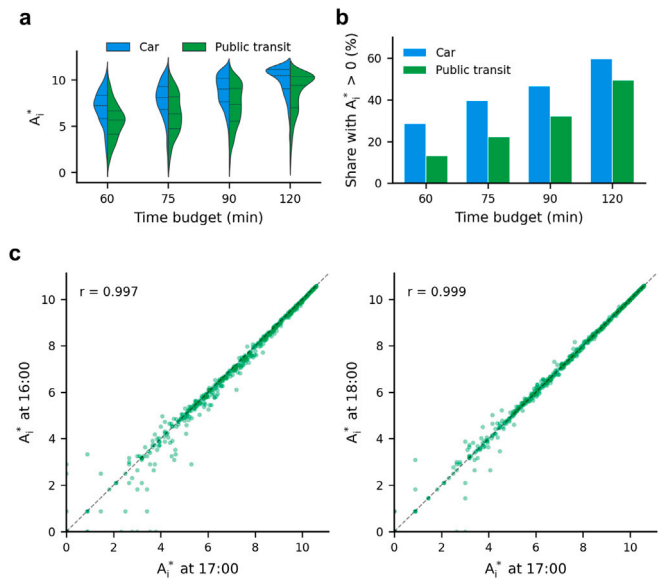


Fig. A.2. Sensitivity of space-time accessibility to parameter choices. a, Distribution of STA (IHS-transformed) by travel time budget, for individuals with $A_i^* > 0$. Split violins compare car (blue) and public transit (green) users. b, Share of individuals with $A_i^* > 0$ by travel time budget and mode. c, Pairwise comparison of STA at different departure hours (16:00, 17:00, 18:00) for public transit users with 90-minute budget. Diagonal line indicates perfect agreement; correlation coefficients shown. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table A.1

SEM model fit across time budget specifications. Departure time is 17:00. CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual. All models use DWLS estimation with sampling weights. $N = 2415$.

Budget (min)	60	90 (baseline)	120
CFI	0.988	0.987	0.986
TLI	0.958	0.954	0.951
RMSEA	0.027	0.029	0.030
90% CI	[0.015, 0.039]	[0.018, 0.041]	[0.019, 0.042]
SRMR	0.013	0.014	0.014

time-constrained individuals, and a generous 120-minute budget representing those with greater temporal flexibility. For each specification, we computed STA using the same methodology and re-estimated the latent variable SEM with identical model structure, covariates, and estimation procedure.

Model fit remained excellent across all time budget specifications (Table A.1), indicating that the model structure is robust to the choice of time budget parameter.

The pattern of effects are consistent across specifications (Table A.2). All three models show a significant positive direct effect of STA on leisure participation and a significant negative indirect effect operating through travel time, yielding a positive total effect. The countervailing mechanism—whereby higher accessibility directly increases leisure engagement but indirectly reduces it by lowering travel time—is replicated under all budget assumptions.

Effect magnitudes vary with the time budget but with stable directions and strengths (Fig. A.3). These findings support the 90-minute threshold as an appropriate balance between capturing meaningful accessibility variation and avoiding floor or ceiling effects, while confirming that the substantive conclusions are robust to reasonable alternative specifications.

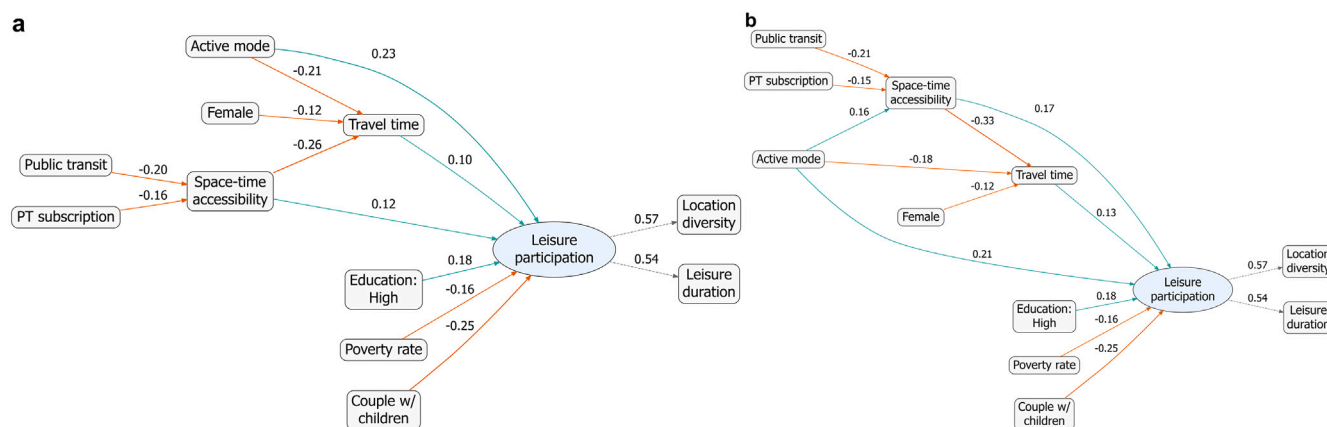


Fig. A.3. Path diagrams for SEM sensitivity analysis under alternative time budget specifications. a, Restrictive 60-minute travel time budget. b, Generous 120-minute travel time budget. Standardized coefficients shown for paths with $p < 0.05$ and $|\beta| > 0.10$. Teal arrows indicate positive effects; orange arrows indicate negative effects. Arrow thickness proportional to effect magnitude. Dashed lines denote measurement model loadings. The latent leisure participation construct is indicated by location diversity and leisure duration. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table A.2

Effect of space–time accessibility on leisure participation across time budget specifications. Standardized coefficients reported for STA (A_i^*) effect on latent leisure participation. Direct effect: STA $\rightarrow$ Leisure participation. Indirect effect: STA $\rightarrow$ Total travel time $\rightarrow$ Leisure participation. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Effect	60 min	90 min (baseline)	120 min
Direct	0.125***	0.181***	0.165***
Indirect	-0.027**	-0.043**	-0.042**
Total	0.098***	0.138***	0.123***

Data availability

The data used in this study were provided through participation in the NetMob 2025 Data Challenge (Chasse et al., 2025), under a non-disclosure agreement (NDA) between all authors, Inria with IFPEN. Due to licensing terms and privacy constraints governed by the European General Data Protection Regulation (GDPR), access to the data is restricted. Venue locations and categories can be retrieved from Overture API. Census data (income) were collected from Institut national de la statistique et des études économiques (INSEE) that is publicly available. GTFS data were collected from `transport.data.gouv.fr` that are publicly available. All data were utilized in accordance with the terms of service specified by their respective provider.

Python (version 3.11) code and R (version 4.5.1) code were used to analyze and visualize the data. The accessibility-related travel times were calculated using *r5r* (version 2.3.0). The code required to reproduce our results is publicly available at [GitHub](#).

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