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**Title:**

What triggers selective daily mobility among older adults? A study comparing trip and environmental characteristics between observed path and shortest path.

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**Highlights**

- Among older adults, walkers compared to car drivers make higher detour percentage
- Environmental characteristics of observed vs. shortest path vary by transport mode
- Walkers seek walking-friendly areas with more street connectivity and low-speed areas
- More access to greenness and amenities entices older adults to make longer detour

**Abstract (149 words):**

Interest is growing in neighborhood effects on health beyond individual's home locations. However, few studies accounted for selective daily mobility bias. Selective mobility of 470 older adults (aged 67-94) living in urban and suburban areas of Luxembourg, was measured through detour percentage between their observed GPS-based paths and their shortest paths. Multilevel negative binomial regression tested associations between detour percentage, trips characteristics and environmental exposures. Detour percentage was higher for walking trips (28%) than car trips (16%). Low-speed areas and connectivity differences between observed and shortest paths vary by transport mode, indicating a potential selective daily mobility bias. The positive effects of amenities, street connectivity, low-speed areas and greenness on walking detour reinforce the existing evidence on older adults' active transportation. Urban planning interventions favoring active transportation will also promote walking trips with longer detours, helping older adults to increase their physical activity levels and ultimately promote healthy aging.

**Keywords:**

Selective daily mobility bias

Walking

Global Positioning System

Detour percentage

Environmental exposures

Older adults

# 1 Introduction

Promoting and maintaining good levels of daily mobility in older age are key challenges of healthy aging. Research found good mobility levels to be a factor of increased physical activity and reduced functional limitations [1]. Moreover, daily mobility allows older people to engage in numerous activities and to maintain their social networks thus fostering well-being [2] and quality of life [3].

Over the past decade, assessing the effects of environmental exposure on older adults' health has evolved from the residence-centered approach as assessed by the life-space concept used in environmental gerontology [4], [5] to the activity space concept [6] which acknowledges the importance of individuals' daily mobility [7], [8]. Indeed, in addition to the environmental characteristics of their direct residential neighborhood, older adults are exposed to numerous and contrasting environments in the course of their daily mobility, which contribute to shaping their health. This shift from a static to a more dynamic exposure assessment was accompanied by significant methodological evolutions to investigate individual's daily mobility patterns from travel diaries, to map-based questionnaires of visited locations. An increasingly popular method relies on trackers such as smartphones or GPS to obtain fine grained spatial and temporal data [9]–[12].

However, place and health studies using daily mobility data, and especially real-time data such as GPS information, are particularly subject to the selective daily mobility bias, which blurs the relationship between the environment and the outcome of interest [8], [13]. In studies looking at the environmental correlates of active or motorized transportation, the selective daily mobility bias refers to when people choose a specific environment that fits with their preference for a specific transport mode [14]: for instance choosing a walking-friendly or car-friendly environment because of ones' willingness to walk or drive. Thus, their preference and attitude towards travel behavior may affect their choice for routes exposed to the most fitting environments. As a result of this bias, it is not only the environmental attributes that encourage people to use a specific mode of transport, but also people's willingness to walk or drive that lead them to seek walking-friendly or car-friendly itineraries. This mobility behavior may be "both an outcome of exposure, as well as a driver of exposure" [15, p. 11]. In that specific case, identifying the environmental factors that determine

transport behavior by accounting for environmental exposure solely along a participant's observed path may result in spurious associations.

Few studies have developed empirical strategies to mitigate such bias [16]–[19]. Different approaches have been proposed [13], [20]. One of them, targeting exclusively GPS studies, consists of correcting the measures of environmental exposures by computing measures of spatial exposure to environmental attributes along the GIS-modelled shortest path between activity locations, instead of the GPS-observed path. Indeed, as argued above, the observed paths and associated attributes are expected to reflect individuals' preferences. In an investigation with children, Burgoine and colleagues (2015) examined the associations between body mass index (BMI) and environmental characteristics (e.g. access to facilities, road safety, land use mix, street connectivity) measured in a 100-meters buffer along children's observed and shortest path from home to school. The authors observed no associations between the BMI and observed path exposures or shortest path exposures, and concluded the absence of selective daily mobility bias. Although it was argued that this absence of selective daily mobility bias might result from the quite distal mechanism linking the environmental exposures and the outcome of interest (BMI) [19], this result also questions whether and how the GIS-modelled shortest path and GPS-observed (preferred) path differ in terms of characteristics.

To our knowledge, few studies in place and health research focus on the environmental correlates of selective daily mobility, or in other words, the detour from a shortest path. Existing studies from the body of transportation research focused on commute routes whether to work [21] or school [22]–[24]. Other studies investigated the environment correlates of route choice for adult cyclists for transport [25]–[27]. However, these conclusions on active transport preferences among youth and adults or on commutes trips with more constraint in time and space [28], may not be relevant to older adults' mobility behavior or to their travel for other purposes.

Using precise GPS-based information on trip paths from a population of older adults, in this paper, we first examine the relationship between the environmental exposure difference of observed and shortest paths and the transport modes, which reflects the selective daily mobility bias. Second, for both motorized (car) and active transportation (walk) modes we investigate how observed paths

differ from their corresponding shortest path, with a focus on non-work trip purposes. Our approach quantifies the trip detour, expressed as the percentage of the distance difference between the observed and the shortest path.

We further explore four hypotheses: First, the environmental exposure differences between the observed and the shortest paths vary by the transport mode of the trip (H1), suggesting that while walking or driving their car, individuals' might seek for specific walking-friendly or car-friendly environments, which further indicates a selective daily mobility bias. Second, trip characteristics, such as transport mode, time spent at the destination, proximity to the place of residence or peak hours predict the detour percentage (H2). Third, the exposure difference to environmental characteristics measured along the observed path and the shortest path predict the detour percentage (H3), thus revealing individuals' preferences for specific environments [22]. Fourth, the associations between the environmental exposure differences and detour percentage vary by transport mode (H4) thus illustrating the extent to which individuals are prone to deviate from the shortest path to select daily paths with environmental characteristics that align with their transport mode. In addition to its methodological relevance on the importance of accounting for the selective mobility bias, this work sheds light on the environmental factors that support daily and active mobility, within a population of older adults for whom short-distance utilitarian walking trips are key in maintaining good physical and mental health.

## 2 Material and methods

### 2.1 Study design

This study is part of the Contrasted URban setting for Healthy Ageing (CURHA) project, and based on a cohort of 471 adults over 65 years of age in Luxembourg [29]. The participants were interviewed between April 2015 and January 2016, 80% of them were recruited in June, July, September, October or November 2015. The sample was assembled randomly from social security files and stratified by age and gender, and along spatially contrasted strata representing different

degrees of urbanity [30]. The participants answered questionnaires covering their health, physical activity and mobility. They also carried an integrated Global Positioning System (GPS) and accelerometer tracker (SenseDoc multisensor, Mobysens Technologies Inc.), during their trips and indoor and outdoor activities for 7 days. The CNPD (National Data Protection Center, Luxembourg) delivered ethical approval (Decision 408/2014) and all participants provided written informed consent.

## 2.2 Environmental characteristics

Hypotheses and expected directions of the associations between environmental characteristics and detour percentage are presented in Table 1.

*Environmental exposures* were measured within a 100 m buffer along observed and shortest paths [16], [31]. Four environmental variables were computed using python scripts: street connectivity, amenity count, greenness, and low-speed areas (see Table 2). For each environmental variable, we calculated the exposure difference between observed and shortest paths.

## 2.3 Observed paths

*Trip detection.* We used a kernel density algorithm exploiting raw GPS data where the GPS epoch was set to 1 second. From the set of GPS points of each participant, the algorithm built a raster of point density. Peak densities were interpreted as visit locations, whereas the dynamic portions are identified as trips. A minimum duration threshold of a 5 minutes stay was set to define a visit [32]. To exclude inaccurate GPS location, the upper 5% of the position dilution of precision (PDOP) values were excluded before the trip detection step. The detection script was run with its default parameters and raw data was down sampled to 5 seconds [33].

*GPS points filtering.* The GPS points of a trip had to satisfy different criteria for distance (<67 m) and altitude difference (<6.7 m) between two consecutive points (1 s) [34], [35] and speed limit (<140 km/h). We discarded every trip with points above these thresholds, as random manual checks identified that these criteria reflect a flaw in the trip (see Figure 1). We removed the circular

trips for which we were not able to model a shortest path between two different locations because, in those cases, no comparison could be made to the observed trip. Trips crossing the national borders of Luxembourg were excluded.

*Mode of transport prediction.* GPS data and accelerometer data were combined to predict for each trip segment the associated transport mode (i.e., car, walk, bus, bike, train). GPS and accelerometer data were extracted from the SenseDoc device. The acceleration data for the three axes was first converted into activity counts which reflects the level of physical activity at each 5 second epoch. For GPS variables, raw accelerometer variables, and activity count variables, measures of central tendency (e.g., median) and dispersion (e.g., minimum and maximum) were derived per trip. A total of 377 measures were then used to predict the transport modes using random forest models developed and validated previously [36]. The transport modes retained for this study were 'car' and 'walk'.

*Map matching of observed paths.* The temporally consecutive GPS points of a given trip were converted into linear paths. As some observed paths appeared to have shifted off the road network, a map matching step was performed [16]. A first attempt to perform a snapping of the points on the roads network in a Geographic Information System (GIS) yielded erroneous trajectories as points near an intersection were not snapped accurately. We then used a map-matching algorithm, that allowed us to find the most plausible snap for each point taking into account the consistency of the whole itinerary. This step involved requests to the match service of a local server of Open Source Routing Machine [37]. This service matches the GPS points to the road network in the most plausible way. The radius parameter, which is used to define the candidates on the GIS roads around the GPS points was set to 50 m [27] and yielded consistent tracks. The server used an OpenStreetMap (OSM) road network archive. This step was performed on driving and pedestrian networks with the predicted mode of transport. It allowed paths cutting through areas such as parks, sport fields, etc., to be detected and removed.



## 2.4 Shortest path

Shortest paths were calculated between the origin and destination of each observed path with the routing service of a local Open Route Service (ORS, version 6.0.0) server [38]. The optimization criterion was the metrical distance [16], [22], [23], [26]. No other road characteristics, such as speed limits or width, were included. The routing used driving and pedestrian networks with the respective predicted mode on the OSM road network archive.

## 2.5 Trip characteristics

*Trip detour percentage.* The length of the shortest path and the observed (snapped) path were computed. The detour percentage is expressed as the ratio of the length difference between the observed path and the shortest path, divided by the length of the shortest path, and multiplied by 100.

*Duration at destination* was calculated for each trip and expressed in hours, including time spent at home between last trip and first trip the next day.

*Trips that overlapped peak hours* (6:30 to 8:30 am and 5:00 to 7:00 pm) were identified based on the trip timestamps.

*Trip to home (vs. other destinations).* The visited location with the maximum summed visit duration was assumed to define home. The match was verified with the geolocalized address from the questionnaires, except in 4 cases for which the home location had to be corrected manually. A variable was set to '1' for trips heading to the home location, '0' for any other destinations.

*Proximity to home* was expressed as the part of the 100 m Euclidean buffer along the observed path that intersects with a 500 m Euclidian buffer around the home location.

Hypotheses and expected directions of the associations between trip characteristics and detour percentage are presented in Table 1.

## 2.6 Individual covariates

Age in years was a continuous variable. Being male, living alone and having a valid driving license were coded as binary variables: yes or no. Education was divided into three categories: none or primary education; secondary education; post-secondary education. A composite score of physical and mental health was computed based on the Medical Outcome of the 36-Item Short Form Health Survey (SF-36) [39]. Residential self-selection bias [40] was taken into account by questioning participants as to whether, when they moved to their current residence, they considered it important to live in a neighborhood that was i) pleasant to walk in and ii) convenient for driving.

## 2.7 Statistical Analysis

*Analytical sample.* From the initial sample of 471 participants from the CURHA study, 10,525 trips of 447 participants were detected. Some 1,758 trips occurring at least in part outside Luxembourg were discarded as some environmental variables were available for Luxembourg only. We filtered out 2,165 trips not satisfying the distance between GPS points, altitude difference, and speed criteria. These removed trips mainly include those with gaps after the GPS signal was lost (see Figure 1). The 1,315 circular tracks were irrelevant to our study and excluded. Some of them may represent recreational trips (e.g. going jogging, walking a dog), or artefacts loops that do not correspond to any actual trip. After the transport mode prediction, 557 trips had either undefined mode (N=531) or a mode different from car or walking and were therefore excluded. In 188 cases the map matching step failed. Especially, the map matching step highlighted paths cutting through areas without any roads (such as parks or sport fields), and generated sub-paths that could not be compared with a shortest path (see Figure 2). The modeling step of shortest paths failed for 19 trips that were excluded. The 26 individuals who had not answered all the questions accounted for 234 trips, which were excluded. Finally, the 99 percentile of the detour percentage was excluded representing 44 trips (detour percentage of car > 326%, and for walking >687%) as they mainly accounted for outliers and unrealistic values of detour percentage. Notably, 419 trips had shortest path longer than the observed path due to the avoidance of some street restrictions (e.g., forbidden access). As 90% of these negative detours percentage reflected a difference less than 13 meters

between the observed and the shortest paths, these trips were kept in the model with a detour percentage value set to zero. The final sample counted 4,245 valid trips made by 357 participants.

*Regression models.* Since the difference between each observed participant trip and its associated shortest path was the unit of analysis, we modeled the percentage of trip detour. The over-dispersion of the outcome and the Akaike Information Criteria supported the need to use a multilevel negative binomial model rather than a multilevel Poisson or multilevel linear model. The negative binomial regression estimates the proportional change in the percentage of trip detour associated with one unit increase in the trip characteristics and environmental variables, with estimates interpreted as rate ratio (RR). Since each participant performed multiple trips, random effects account for within individual correlation in the trip detour. Individual socio-demographics were included in all models. All variables were tested for multicollinearity. No multicollinearity was detected (Tolerance > 0.48; VIF < 2.08). We opted against model selection. Thus, all individual variables, trip characteristics and environmental variables were kept in the model. Lastly, we tested separately the multiplicative interaction between the environmental variable and the mode of transport. At this stage, we opted for model selection: if the p-value for an interaction was below 0.05 (Type III test of effect), the interaction term was kept in the model. All analyses were performed using SAS 9.4 (SAS Institute Inc., Cary NC).

## 3 Results

### 3.1 Final sample characteristics

The participants in the final sample were on average 75.7 years old and 55% male (Table 3). Participants whose highest degree was secondary school constituted 49% of the sample, 28% lived alone and 79% had a valid driving license. When they moved to their respective residential neighborhood, 53% of the sample found it important to live in a walkable neighborhood and 51% to live in a neighborhood that was easy to drive in.

The participants made an average of 10.7 valid trips (sd = 7.8). They spent on average 4.0 hours (sd = 8.2) at their destination. Overall, 20.1% of their trips took place during peak hours, 30% in proximity to home and 35.4% of trips were trips to home.

### 3.2 Characteristics of observed path, shortest path and detour percentage

On average the length of the observed path was 3.4 km (sd = 4.96), with the shortest path being 2.9 km (sd = 4.28) (Table 4). A comparison by transport modes showed that the length of the observed path was, on average significantly longer for car trips, with 5.5 km (sd = 5.82), than for walking trips, with 0.72 km (sd = 0.88). The mean detour length varied significantly between car driving and walking: about one third of the pedestrians detoured more than 50 m whereas one third of the car users detoured more than 450 m. The detour percentage from the shortest path was on average 21 % (sd= 55) and varied significantly by transport mode.

Overall, environmental characteristics measured along the observed path and the shortest path varied by transport mode (Table 5). The observed paths, compared to the shortest path, revealed a significantly higher exposure to amenities, street connectivity and greenness, and a significantly lower exposure to low-speed areas. Moreover, the exposure differences in the street connectivity and low-speed areas significantly vary by transport mode. Indeed, for walking trips, the observed paths account for more low-speed areas than the shortest path, while the opposite is observed for car trips.

### 3.3 Associations between trip characteristics, environmental characteristics and detour percentage

After we controlled demographics and residential self-selection variables, walking, as compared to driving, is associated with an increase in the detour percentage. Contrastingly, trips realized in proximity to home are negatively associated with the percentage of detour (Table 6). We observed no association with the length of the shortest path, the number of hours at destination, the trip overlaps with peak hours, and the type of the destination (trip to home vs. other).

For the associations with environmental characteristics of trips, the detour percentage is significantly associated with the amenity and greenness exposure difference between the observed and the shortest path: more amenities and greenness along the observed path correlate with greater detour percentage.

We found multiplicative interactions between the transport mode and the environmental exposure difference between the observed and the shortest path. A positive amenity count difference between the observed and the shortest path (i.e., the observed path has exposure to more amenities than the shortest path) correlates with a higher detour percentage among walkers than among car drivers (Figure 3). More low-speed areas along the observed path, compared to the shortest path, correlates with a greater detour percentage for walking trips, and a lower detour percentage for trips made by car (Figure 4).

## 4 Discussion

By analyzing the detour percentage of trips and the environmental exposure difference, we investigated the individual environmental and mobility preferences. Examining these preferences by transport modes provides valuable insights on the determinants of selective daily mobility for non-work trip purposes, among older adults in Luxembourg.

### 4.1 Main findings

Overall, the environmental characteristics of observed and shortest path differs in terms of exposure to amenities, street connectivity, greenness, and low-speed areas. The significant differences in exposures to street connectivity and low-speed-areas between the observed and the shortest path by transport mode support evidence of potential of selective daily mobility bias (H1).

Our results suggest a potential reverse causality as walkers seek walking-friendly environments with more low-speed areas and better connectivity. On the other hand, car users seek car-friendly environments by favoring high-speed areas rather than what shortest paths offer. These results

further indicate a risk of overlooking potential selective daily mobility bias in studies accounting only for the observed path, and not including the shortest path, while investigating the environmental correlates of walking, driving, or transportation-related physical activity. More generally, these results echo the other few studies that observed evidence of selective daily mobility bias in the association between environmental exposures and recreational walking [41], or sport practice [19].

The mean trip detour of 21% observed in this study, all modes of transport considered, is consistent with the order of magnitude found across different populations in previous studies showing a detour percentage of 27% among adult commuters in Cambridge (UK) [21], and 21% among children for home-school trips in Norfolk (UK) [23]. Studies on adult cyclists observed a detour of 7.6% on average in Graz (Austria) [26] and trips of 13.5% higher length in Columbus, Ohio (USA) [25]. One study in Amsterdam region (The Netherlands) noted no significant detour percentage for active trips to school among children [22].

In line with our second hypothesis (H2), certain trip characteristics predict the detour percentage. We found a strong correlation between the detour percentage and the transport mode, with a significantly greater detour percentage for walking than for driving. We hypothesized that walking allows individuals to deviate more easily from the shortest road dependent on external stimuli (such as pollution, noise, traffic incident, etc.) with fewer network restrictions such as no-entry rules [42]. A qualitative investigation of older adults' driving behaviors in a Midwestern state in the USA stresses that they are more prone to use direct roads and reject alternative itineraries [43]. This relationship between the detour percentage and the transport mode was also quantitatively investigated by [21], [23]. However, their results show a greater detour for car use than for walking. This contradictory finding might be linked to the authors' observed negative mean detour for walkers (i.e., shortest paths are longer than the observed path), indicating their participants used paths with roads that were missing in the modelled network. Time constraints linked with the nature of their trip purpose (i.e., commuting, travel to school) may also contribute to the explanation of such opposing results [21], [23].

No association was found with the type of destination (trip to home vs. other), although the proximity to home was associated with the detour percentage. Previous works found an association with the

type of destination and the transport mode [30] or a difference in the overlap between observed and shortest routes from home to school as compared to those from school to home [24]. This association indicates that the type of destination, and especially the place of residence, may have an effect on the route choice and thus the likelihood to take a detour.

The time spent at destination was not associated with the detour percentage. Another study suggested a relation between the time spent at destination and the mobility behavior [44]. Trips with mandatory purposes compared to discretionary ones revealed large differences in the ratio between travel time and time spent at destination. Our dataset does not distinguish between mandatory and discretionary purposes, as detected trips do not specify any purpose at all. (see Strengths and Limitations). Finally, we observed no association between peak hours' trips and the detour percentage. Although scarcely investigated as a potential correlate of trip detour, peak hours were positively associated with cyclists' trip detours in a population of adults in Ohio (USA) [25]. Older adults might be less subject to peak hours' constraint, which might explain the lack of significant associations with trip detour in our study.

As expected in our third hypothesis (H3), environmental exposure differences between the observed and the shortest path are associated with the detour percentage. Overall, observed paths were greener, with greater access to amenities, greater street connectivity and fewer low-speed areas. Greater exposure to greenness and street connectivity along the observed path, as compared to the shortest path, correlate positively with higher trip detour percentage. In line with our findings, aesthetics characteristics reflecting the presence of green (trees, parks) amenities have often found to be related to detour [26].

Our results confirm our fourth hypothesis (H4) that there is a multiplicative interaction between the difference in exposure to environmental characteristics between the observed and the shortest path (e.g., number of amenities, low-speed areas) and the transport mode in their association with the detour percentage. In our study, an increase in exposure to low-speed areas along the observed path, as compared to the shortest path, is associated with an increase in detour percentage among walkers, and a decrease in detour percentage among drivers. In other words, walkers are likely to make detours to seek safe paths with limited traffic speeds, while drivers make even larger detours

to seek environments with fewer low-speed areas. This association is consistent with the findings from Mizen and colleagues where the road typology was associated with the detour among children's walks between schools and their homes [24]. Similarly, in the Netherlands, children were more likely to walk to school along residential roads where speed was limited to 30 km/h [22].

While this study focuses on the determinants of selective daily mobility, our results on the environmental correlates of walking trip detour are consistent with existing evidence on older adults' active transportation [1], [45]. They reinforce previous conclusions on the positive effects of the presence of amenities that provide a diverse spectrum of destinations [46], a good street network connectivity [47] and greenness [48]. The low-speed areas were also shown to be positively associated with walking since they providing a safe environment to older adults [49]. Urban planning interventions aiming at fostering active transportation will then also help promoting walking trips with longer detours. Those interventions would in turn help older adults walk longer distance, increase their overall physical activity level, and ultimately promote healthy aging.

#### 4.2 Strengths and Limitations

The predictors of selective daily mobility have rarely been investigated in place and health research, while transportation research has produced more evidence of individual preferences with the investigation of "route choice" modelling. However, most studies are focused on specific trip purposes such as commuting to work [21] or traveling to school [16], [22], [24], or on specific transport modes such as bicycle [25]–[27]. By examining the correlates of selective daily mobility for multi-purposes non-work trips, performed by motorized and active transport modes among older adults, this study provides a more comprehensive approach to individual preferences in terms of daily mobility behaviors in a less studied segment of the population. By testing the interactions between the environmental correlates of trip detour and transport modes, this study is one of the few attempts to qualify and quantify how individuals' preferences for walking may be translated in terms of exposure to environmental characteristics and detour percentage. The study relied exclusively on objectively measured information regarding observed path, trip characteristics, and environmental exposure. The chosen methodology of automatically detecting trips and cleaning



the observed paths allowed us to make use of a large set of trips without involving manual intervention. We believe this systematic approach based exclusively on objectively measured data heightens the internal validity of the study.

This study has the following limitations. Measurement of environmental exposure along the observed and the shortest path used buffers of 100 m along the paths, as observed in other studies [16], [21], [31]. Other studies have used smaller buffer sizes, 15m [25], 25m [22], [26], 50m [27]. Using a 100 m buffer might have led to an inaccurate exposure during trips [22]. Moreover, environmental conditions beyond 100 m around each trip origin and destination were disregarded, although we cannot exclude their potential role in predicting the detour percentage. As observed by Dalton and colleagues (2015), some GPS paths were shorter than their theoretically associated GIS-based shortest path. This issue arose when participants used shortcuts or paths not referenced in the road network. To overcome this issue, we computed the shortest paths by transport mode, using a pedestrian network for walking trips, and the road network for driving trips. This process prevented the inclusion of restricted roads for a specific transport mode, such as a pedestrian path across a park for drivers, or the use of highways for pedestrians. Also, trips were detected with their origins and destinations based on a kernel-density algorithm [32]. Therefore, we cannot rule out that the algorithm may have overseen some trips, or that origins or trip destinations might be part of larger trip chains, with multiple destinations. We excluded from this study public transport and cycling. Two reasons grounded this decision: First, the public transport routes are highly constrained by time schedule and fixed by the operator. These constraints limit individuals' route choices. Second, mode detection revealed a small proportion of public transport (0.4%) and cycling use (0.06%). Given the sample size of trips relying on cycling and public transport, statistical analyses and especially interaction analyses would have been underpowered in our study. Circular trips were excluded as their shortest path would be of zero length. This choice meant excluding a range of trips varying from loops artifacts generated by the trip detection step to recreational trips (e.g., walking a dog) or very specific transport trips (e.g., accompanying or dropping off car passengers). The seasons and weather could also influence the older adults' mobility, as shown in other studies [50], [51], and should be tested as correlates of trip detour in further modeling. Futures

studies could also consider additional individual correlates of trip detour, such as traveling alone or accompanied.

Finally, the strength of the association between the environmental characteristics and the percentage of detour may be age-specific. As such, replication studies on other age categories are needed to assess the consistency of the results for different age categories.

## 5 Conclusion

This study is one of the very few empirical investigations to account for the selective daily mobility bias in place and health research, and goes a step further by determining to what extent older adults engage in selective mobility behaviors and the determinants of those behaviors. By identifying the trip characteristics and environmental correlates of trip detours from the shortest path, this study shed light on older adults' preferences during their daily mobility. Differences in environmental exposures between the observed and shortest path by transport mode support the evidence of selective daily mobility bias, and invite caution in studies linking accessibility to specific environmental conditions along participants GPS tracks for specific transport modes. In addition, greater access to green environment, the presence of amenities, roads with greater connectivity, seem to entice older adults into making greater detours. Interestingly, low-speed areas seem to foster greater detours among walkers and reduced detours among drivers. Integrating the environmental correlates of walking detours into broader urban planning strategies to promote walking could contribute to enhancing walking among older adults while increasing the walking time by providing supportive environment for walking detours. The increase in walking time through walking detours may also help people to spend more time in the corresponding neighborhood environment, which in turn could help people develop a stronger sense of belonging and familiarity to this environment [52]. This increased familiarity with a place could help compensate functional loss when physical and psychological changes will occur and ultimately favor aging well in place [53]. This study also strengthens current policy recommendation to promote walking among older adults and provide supporting elements to favor aging in place policies [54].

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## 7 Tables

Table 1: Hypothesis of effects of trips variables and environmental exposure difference between the observed and the shortest path.

Variable	Expected direction	Hypotheses
<b>Trips variables</b>		
Shortest path length	negative	The detour percentage is expected to decrease with increasing shortest path length as suggested in one study about cyclists [25, p. 1]
Walk (vs. Car)	positive	Walking offers more flexibility in the route choice due to fewer constraints as compared with driving which should follow traffic regulations (one-way, restricted access) and thus is associated with increased detour percentage. Older drivers prefer routes that are direct [43]
Proximity to home	positive	As individuals spend a large share of their time in their residential neighborhood they are expected to have a better spatial knowledge of this neighborhood (as compared to more distant areas) thus giving them the propensity to make greater detour. The elderly travels short distance typically within the immediate neighborhood [55]"
Number of hours at destination	positive	A greater time spent at destination is expected to be associated with greater detour percentage as such destinations are unlikely in the middle of larger trip chains.
Trip overlaps peak hours	positive	Independently of the transport mode, we expect trips during peak hours correlate positively with detour percentage. Indeed, drivers may choose longer itineraries involving secondary roads to avoid traffic congestion. Pedestrian may as well avoid heavily congested main roads to escape negative externalities (air and noise pollution, collisions). Older drivers preferred to avoid school zones in the morning and downtown in the evening" [43]
Trip to home (vs. other destinations)	positive	Trips to home are less likely to be constrained by time and thus allowing more flexibility to make detour
<b>Environmental exposure difference between the observed and the shortest path</b>		
Amenity count difference	positive	A large set of amenities provide attractive environment to travel even without purchase intention. A positive difference is associated with longer detours. Such association might be stronger among walker as compared to drivers. Walking is associated with the access to amenities [30]
Street connectivity difference	positive	A denser network provides more alternative itineraries and detour possibilities. A positive difference is expected to correlate positively with detour percentage
Greenness index difference	positive	A greener environment provides more pleasant landscape with restorative qualities. We expect that a positive difference in greenness exposure is associated with high detour percentage. Such association might be stronger among walker as compared to drivers.
Low-speed areas difference	Positive for walkers & negative for drivers	A low traffic intensity and a high traffic safety related positively with transportation walking. We expect that a positive difference in the share of roads $\leq 30$ km/h relate positively with the detour percentage among walkers. A negative association among drivers is expected.

Table 2: Description of environmental variables, and data sources

<b>Variable</b>	<b>Description</b>	<b>Source</b>
Street connectivity	Count of intersections (above three-ways) within the observed and shortest path buffers	Base de données topographique coming from Administration du Cadastre et de la Topographie (2008), and OpenStreetMap (2014)
Number of amenities	The amenity count within each buffer reflects a variety of categories of shops and services of daily and weekly resorts [30]. This includes restaurants and cafes, medical and dental offices, pharmacies, markets, bakeries, butcher shops, sports facilities, cultural venues, tobacco and newspaper offices.	LISER (2013)
Greenness index	Index ranking from 0 to 1, based on a formula from. It is composed of a 4- weighted classes Soil Adjusted Vegetation Index (SAVI) using radiometric data from Red and Near Infrared bands [30], [56]	Landsat 8 reflectance data from June 2014, provided by the U.S. Geological Survey. The imagery is free of clouds
Low-speed areas	Ratio of the length of the roads limited to 30 km/h on the total length of the road network in a buffer of 100 m of the observed and shortest path. For roads without a speed attribute, we considered a default speed limit of 30 km/h for roads described as: footway, living_street, pedestrian, residential_link, road, service or track.	OpenStreetMap network (January 2016)



Table 3: Socio-demographic characteristics of the participants (N=357)

<b>Variables</b>	<b>Category</b>	<b>%</b>	<b>Mean</b>	<b>SD</b>	<b>Min</b>	<b>Median</b>	<b>Max</b>
Sex (being a man)	no	45%					
	yes	55%					
Age			75.7	6.0	67.0	75.0	94.0
Living alone	no	72%					
	yes	28%					
Education	none or primary	29%					
	secondary	51%					
	post-secondary	20%					
Valid driving license	no	21%					
	yes	79%					
SF-36 Physical Health composite score			56.6	10.6	26.0	60.0	70.0
SF-36 Mental Health composite score			62.1	9.8	22.0	64.0	78.0
Importance of the ease to walk in the neighborhood in the choice of moving in the current dwelling	not important	47%					
	important	53%					
Importance of the ease to drive in the neighborhood in the choice of moving in the current dwelling	not important	49%					
	important	51%					

Table 4: Distances of observed and shortest path and detour percentage (N = 4,245), by car (N = 2,356) or walk (N = 1,889)

	Mean (SD)	Min	10 <sup>th</sup> percentile	90 <sup>th</sup> percentile	Max	T-test p-value
<b>Observed path length (km)</b>						
all	3.34 (4.96)	0.01	0.15	9.04	57.46	
car	5.45 (5.82)	0.01	0.69	12.79	57.46	
walk	0.72 (0.88)	0.01	0.09	1.71	7.99	<.0001
<b>Shortest path length (km)</b>						
all	2.88 (4.28)	0.00	0.14	8.23	49.71	
car	4.74 (4.99)	0.01	0.65	11.38	49.71	
walk	0.56 (0.60)	0.00	0.08	1.30	5.18	<.0001
<b>Detour (in km)</b>						
all	0.46 (1.19)	-0.66	0.00	1.30	19.61	
car	0.71 (1.50)	-0.66	0.00	2.14	19.61	
walk	0.16 (0.45)	-0.48	0.00	0.47	6.90	<.0001
<b>Detour percentage (%)</b>						
all	21.2 (54.9)	0.00	0.00	52.7	687.1	
car	16.2 (35.3)	0.00	0.00	41.4	326.2	
walk	27.5 (71.7)	0.00	0.00	69.5	687.1	<.0001

Table 5: Environmental characteristics along the observed and shortest paths (N = 4,245), by car (N = 2,356) or walk (N = 1,889)

	Observed path exposure				Shortest path exposure				Exposure difference Observed path - Shortest path <sup>a</sup>			
	mean (sd)	min	max	T-test p-value	mean (sd)	min	max	T-test p-value	mean difference (sd)	95% CI	T-test p-value	
<b>Number of amenities</b>												
all	24.3 (31.3)	1.0	306.0		22.4 (27.3)	1.0	244.0		1.9 (16.8)	<b>1.38</b>	<b>2.39</b>	
car	27.2 (33.0)	1.0	306.0	<.0001	25.6 (29.2)	1.0	244.0	<.0001	1.7 (20.3)	<b>0.84</b>	<b>2.48</b>	0.30
walk	20.5 (28.7)	1.0	205.0		18.4 (24.0)	1.0	164.0		2.2 (10.8)	<b>1.68</b>	<b>2.65</b>	
<b>Street connectivity</b>												
all	6.2 (7.1)	1.0	60.0		5.6 (6.2)	1.0	50.0		0.6 (3.5)	<b>0.49</b>	<b>0.70</b>	
car	8.4 (8.3)	1.0	60.0	<.0001	7.6 (7.1)	1.0	50.0	<.0001	0.8 (4.4)	<b>0.61</b>	<b>0.97</b>	<.0001
walk	3.4 (3.9)	1.0	31.0		3.0 (3.2)	1.0	24.0		0.4 (1.8)	<b>0.28</b>	<b>0.44</b>	
<b>Greenness index (%)</b>												
all	24.3 (18.4)	0.0	100.0		24.1 (18.5)	0.0	100.0		0.2 (3.9)	<b>0.12</b>	<b>0.36</b>	
car	27.0 (14.5)	0.0	70.2	<.0001	26.7 (14.8)	0.0	70.8	<.0001	0.3 (4.7)	<b>0.12</b>	<b>0.50</b>	0.19
walk	20.9 (21.9)	0.0	100.0		20.8 (21.8)	0.0	100.0		0.2 (2.6)	<b>0.04</b>	<b>0.27</b>	
<b>Low-speed areas (%)</b>												
all	49.9 (22.2)	0.0	100.0		50.6 (22.4)	0.0	100.0		-0.7 (6.4)	<b>-0.88</b>	<b>-0.50</b>	
car	45.1 (17.2)	0.0	100.0	<.0001	46.5 (17.3)	0.0	100.0	<.0001	-1.4 (7.1)	<b>-1.68</b>	<b>-1.10</b>	<.0001
walk	55.9 (26.0)	0.0	100.0		55.7 (26.6)	0.0	100.0		0.2 (5.1)	-0.05	0.42	

<sup>a</sup> Exposure differences tested using a paired sample t-tests

Table 6: Associations between trip characteristics, environmental exposure difference between the observed and the shortest path, and detour percentage (N = 4,245)

	RR	CI 95%
<b>Trips variables</b>		
Shortest path length (vs. low)		
middle low	0.94	[0.76 - 1.17]
middle high	0.93	[0.71 - 1.2]
high	0.85	[0.62 - 1.15]
<b>Walk (vs. Car)</b>	1.63	[1.33 - 2]
<b>Proximity to home (1 unit increase)</b>	0.66	[0.51 - 0.86]
Number of hours at destination (1 hour increase)	1.00	[0.99 - 1.01]
Trip overlaps peak hours (vs. no overlap)	0.94	[0.8 - 1.12]
Trip to home (vs. other destinations)	0.94	[0.8 - 1.12]
<b>Environmental exposure difference between the observed and the shortest path</b>		
Amenity count difference (1 unit increase)	1.00	[1.00 - 1.01]
<b>Street connectivity difference (1 unit increase)</b>	1.09	[1.07 - 1.11]
<b>Greenness index difference (1% increase)</b>	1.04	[1.03 - 1.05]
<b>Low-speed areas difference (1 % increase)</b>	0.98	[0.97 - 0.99]
<b>Interaction terms</b>		
<b>Amenity count difference * walk</b>	1.02	[1.01 - 1.04]
<b>Low-speed areas difference * walk</b>	1.03	[1.02 - 1.04]

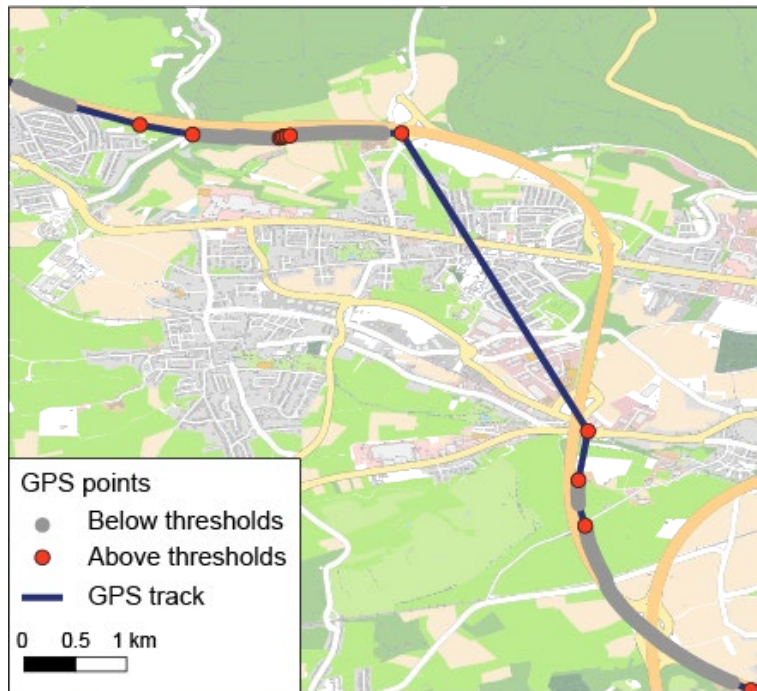
Abbreviations: RR: rate ratio; CI: Confidence interval

Note: Model adjusted for sex, age, marital status, physical health, mental health, individual education, having a valid driving license and residential self-selection for walking and driving.

Note 2: The exposure to one more unit in low-speed areas difference is associated with a lesser detour percentage of 0.98 percentage point.

## Figures

Figure 1. Trip filtering based on their GPS points attributes.



*Note: In this example, either some of the GPS points (in red) exceed the thresholds for distance or altitude difference with their temporally previous points or their measured speed is too high. We therefore excluded the whole trip (in blue).*

Figure 2. Example of one of the 188 excluded observations after the map-matching step resulted in two sub-paths.



Figure 3: Interaction between amenity count difference and detour percentage by mode of transport.

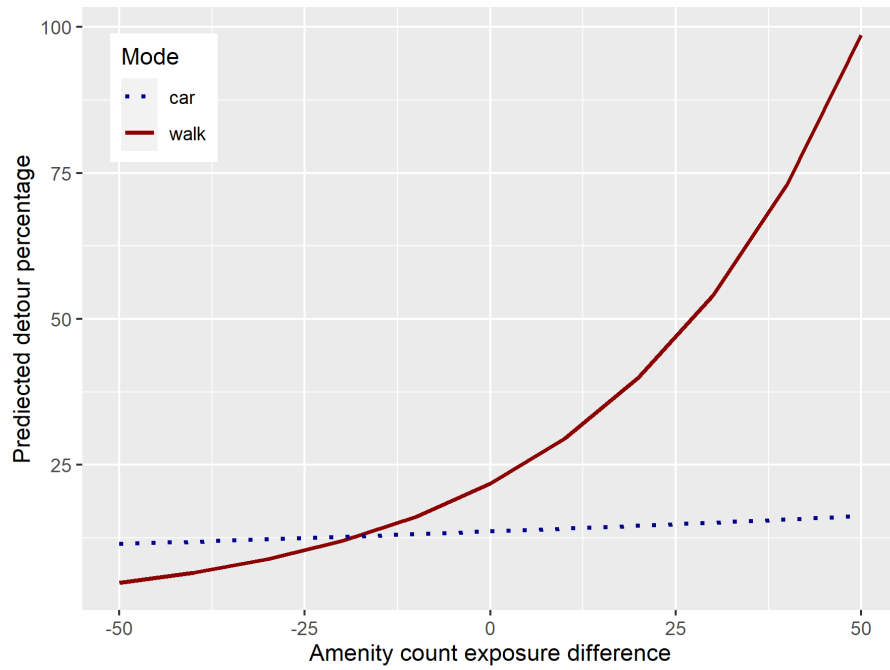


Figure 4: Interaction between low-speed areas exposure difference and detour percentage by mode of transport.

