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The Associations of Street Network and Urban Form with Walking Frequencies

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Abstract

Walking is globally promoted as an urban transport mode that reduces greenhouse gas emissions and increases physical activity. While it is well-known that accessibility at neighbourhood and urban levels impacts walking levels, studies on pedestrian travel behaviour are typically based on area-based measures. Network-based measures of street configuration, connectivity, urban density, and land-use diversity have scarcely been applied.

This paper aims to find associations of network-based connectivity and accessibility measures with walking frequencies. We used a series of multivariable ordinal regressions adjusted for distance to various destinations, building-type diversity, socio-demographic variables, and car ownership. We operationalise connectivity as reach – i.e., the number of streets reached through the network within walkable distances through the network — and density and diversity as weighted reach – i.e., the floor area, population, or retail diversity reached within walkable distances through the network. Street network configurations are described by topological centrality (integration). Results show significant positive associations of reach, attraction reach, and integration with walking frequency, with the best model fits achieved by accessible total floor area and reach within relatively high network radii (1000 m and 9 axial steps), indicating that connectivity and accessibility to a variety of attraction and functions, often beyond administrative borders, encourage walking.

1 Introduction

The health, cost, and environmental benefits of daily walking are well-documented (De Nazelle et al., 2011; Gössling et al., 2019; Lee and Buchner, 2008). Due to these benefits, there is considerable interest in encouraging more people to walk for urban transport and a scientific interest in the relationship between urban form and walking (Saelens and Handy, 2008; Salvo et al., 2018; Smith et al., 2017). The existing literature suggests a positive impact of building or population density, land-use diversity, proximity to destinations, and network connectivity on walking (Smith et al., 2017). These variables closely relate to "walkability" or "pedestrian accessibility," umbrella terms that quantify how urban form facilitates walking.

Research on walkability often uses aggregate area-based measures, such as the number of intersections per census area. Although such measures are conceptually simple, they have limitations in capturing important aspects of fine-grained pedestrian networks and show inconsistent results depending on area size and geometry (Knight and Marshall, 2015). The existence of various connectivity indices has led to further inconsistencies. This is problematic because network connectivity plays a particularly important role in pedestrian mobility (Knight and Marshall, 2015).

Other studies have shown that walking is associated with network-based accessibility measures such as the number of streets reached within a certain distance through the network, so-called "reach" (Peponis et al., 2008) or reach weighted by population, building, or attractions (e.g., Ståhle et al., 2010). While the former accounts primarily for network configurations and connectivity, the latter measures pedestrian accessibility to functions provided by density or diversity. In contrast to area-based measures, such network-based measures are not limited by predetermined boundaries but by the scope of the analysis. Moreover, they account for network configurations and capture the effect of missing connections on connectivity and accessibility.

Despite these advantages, network analysis has primarily been applied to studies on pedestrian distributions and flows (Kang, 2018; Pearce et al., 2021), whereas research on other outcomes, such as mode choice or walking frequencies, is limited. The definition of distances also varies across studies, with authors a) applying metric distances, capturing physical effort, or b) angular and topological distances, capturing the cognitive impedance of turns (Feng and Zhang, 2019). However, little research has been conducted on the most appropriate distance metric for the propensity to walk. Moreover, it remains to be explored whether weighting network measures with land-use variables, such as population or retail, explains the propensity to walk more than network configuration and connectivity alone.

Based on this background, this paper aims to answer the following research questions:

- Are network configurations and network reach significantly associated with the frequency of walking?
- Are there significant differences between metric and topological network measures in explaining walking frequencies?
- Does weighting reach by population, floor area, employees, retail diversity, and building diversity improve the observed model fits for predicting walking frequencies (compared to network reach)?
- Does the impact of network configuration, network reach, and weighted reach on walking differ between high-density urban areas and primarily low-density residential areas?

2 Background

2.1 *Walkability and Pedestrian Accessibility*

There is a multi-disciplinary interest in the relationship between urban form and walking. Urban planning and policies can directly impact urban form, and the walking quality of an environment directly impacts public health and mobility-related emissions. This interest has led to the development of several "walkability" indexes. Although walkability lacks a clear definition, street connectivity, density, and diversity are key variables (Shields et al., 2021). These variables have not only shown positive associations with walking in several studies (e.g., Fonseca et al., 2022; Smith et al., 2017), they are also difficult to change once a city has been built (Dovey and Pafka, 2020). Walkability indices may also include factors related to street quality, attractiveness, comfort, slope, and pollution (Fonseca et al., 2022), which cannot be changed or easily altered after city development (Dovey and Pafka, 2020).

Common measures for capturing connectivity, density, and diversity are area-based. For instance, street connectivity is often measured as block sizes, density of streets or intersections, or link-node ratios per census area, or transport analysis zone (TAZ) (Ellis et al., 2016). However, some authors have argued that such measures do not fully capture important aspects of pedestrian mobility. First, network configurations and connections between individual street segments inside areas are not accounted for (Knight and Marshall, 2015). Second, the definition of the area boundaries is arbitrary, leading to the Modified Area Unit Problem (MAUP; Berghauser Pont and Haupt, 2021, pp. 90-91) — i.e., varying outcomes in density and connectivity calculations based on the chosen boundaries.

Another issue arises when framing walkability from the perspective of pedestrian accessibility or the ease of reaching various relevant destinations, as pedestrians often move beyond formal area units. To account for accessibility, authors have measured the proximity to amenities (Hall and Ram, 2018), while others have developed measures derived from Jacob's (1961) "pool of use," such as walkable catchment areas or "pedsheds" (Ellis et al., 2016; Schlossberg et al., 2006; Dovey and Pafka, 2020). Catchment areas capture areas reachable from specific points, often combined with the cumulative counting of opportunities or network length (e.g., Lahoorpoor and Levinson, 2020; Sarkar et al., 2018). However, these studies did not focus on the configuration of fine-scale pedestrian networks (Shields et al., 2021). For instance, a literature review by Fonseca et al. (2022) on built environment attributes and their influence on walkability identified 132 relevant studies. However, only two accessibility-based studies used road network distances instead of Euclidean distances, and only one study applied a detailed pedestrian network. Road networks may include non-pedestrian roads and lack important pedestrian paths and shortcuts (Ellis et al., 2016).

2.2 *Network Configurations and Topology*

Network configurations have primarily been studied outside the context of walkability, namely, in network analysis and urban morphology. For instance, Peponis et al. (2008) introduced "reach" as an alternative connectivity measure. Reach measures the number or length of street segments reached within a distance threshold from any segment in the network. While reach can be considered a measure of walkability (Ellis et al., 2016), Peponis et al. (2008) described it as a measure of the potential for movement and density. Cooper and Chiaradia (2020) consider it a measure of accessibility.

The concept of reach originates from spatial distances, as addressed in space syntax, a set of theories about spatial configurations grounded in architecture. In basic space syntax, network distances are measured topologically as steps between so-called "axial lines", which are the fewest and longest straight lines needed for modelling a city's street network (Hillier and Hanson, 1984). Subsequent space syntax measures applied segment maps, allowing the calculation of distance as cumulative angular changes on segmented axial maps or more widely available transport networks (Turner, 2007). Applying directional, that is, topological and angular, distances assumes that the number of turns affects pedestrians' spatial cognition and perceptions of length. Thus, directional reach measures the cognitive effort to move around a city (Feng & Zhang, 2019; Legeby et al., 2017). Cooper & Chiaradia (2020) and Feng & Zhang (2019) describe alternative formulations of reach.

Other authors have focused on how the centrality of streets generates pedestrian movement. In urban sciences, "closeness centrality" describes how close a place or street is to everywhere else in the city. The shortest path can be the least metric distance, least cumulative angular change, or fewest topological steps (Hillier and Iida, 2005). The different approaches to centrality share the theory that some places are more important than others and that centrality plays an important role in spatial cognition, route choice, economic activities, urban resilience, and urban vitality (Chiaradia et al., 2012; Hillier, 1996; Porta et al., 2006).

Neither reach nor closeness centrality explicitly considers origins, destinations, or attractions. Movements are assumed to be from "everywhere" in the city to everywhere else within certain network distances (Hillier, 1996). This notion is supported by the observed correlations between reach and closeness centrality with pedestrian flows (e.g., Sharmin and Kamruzzaman, 2018). However, Cooper et al. (2021) pointed out that applying network accessibility assumes some interrelations between accessibility, transport, land use, and density. For instance, reach has been shown to correlate with population and employment densities (Chiaradia et al., 2014; Cooper, 2017; Schön et al., 2024) and the distribution of retail front spaces (Scoppa and Peponis, 2015). Similarly, streets with higher centrality tend to draw more economic activities and pedestrian flows (Hillier, 1996; Porta et al., 2006).

However, as Netto et al. (2012) and Ståhle (2008) pointed out, such interrelations between networks, accessibility, and land use are not a given. For example, retail or new residential areas can be placed in areas with low network density. Thus, several authors have weighted reach by buildings, population, building floor area, or retail (Sevtsuk and Mekonnen, 2012; Ståhle et al., 2010), describing network configurations and other urban form variables, such as density or diversity, as a single accessibility variable. For instance, the number of residents within a walkable distance through a pedestrian network is a measure of connectivity and accessibility, and of population density, as perceived by pedestrians (Marcus et al., 2017). In urban morphology studies, weighted reach is also referred to as "attraction reach", "accessible density", or "accessible diversity" (e.g., Berghauser Pont and Marcus, 2015; Marcus et al., 2017).

Reach, weighted reach, and closeness centrality have been shown to correlate with pedestrian distributions and flows (e.g., Bolin et al., 2021; Kang, 2018; Pearce et al., 2021). However, only a few studies have investigated the associations between these variables and other outcomes. For instance, a few studies have found positive associations between integration and walking mode choice (e.g., Baran et al., 2008; Berhie and Haq, 2017) and walking frequencies (e.g., Koohsari et al., 2016, 2014). Reach has been applied to studies on walking to public transport stations (Ozbil and Peponis, 2012) and schools (Ozbil et al., 2021), as well as on walking activity (Ellis et al., 2016), with all three studies finding positive associations between reach and walking. However, we could find no empirical study applying topological reach and no study relating metric or weighted reach to walking frequencies.

Our study adds to the existing body of knowledge by examining the associations of network reach, network configurations, and weighted reach with walking frequencies. We compare the impact of the network measures with reach weighted by population, floor area, and diversity in two areas with different urban densities, applying both metric and topological distances.

3 Methods

3.1 Study Location

Trondheim is Norway's third-largest city, with a population of 211,246 (Trondheim kommune, 2022). The city layout is shaped by a historical centre with an irregular network and narrow streets from the medieval ages, combined with a more regular street network with broad, straight main streets designed in 1681 by Johan Caspar de Cicignonin. The city expanded over time by merging with neighbouring municipalities.

Trondheim's modal share for walking in 2018/19 was 27%, which was 7% higher than the national average (Grue et al., 2021). However, similar to many cities globally, Trondheim aims to increase its share of walking and active mobility (Knapskog and Peters, 2021).

Figure 1 shows a) Trondheim's municipal border, b) "tettsteder", urban areas defined as a continuously built-up area meeting thresholds for minimum population and a maximum distance between houses (Statistics Norway, 2002) and c) Trondheim's buildings coloured by floor area density, measured as the total floor area (BRA – bruksareal) reached within 1000 m through the network (see Section 3.5).

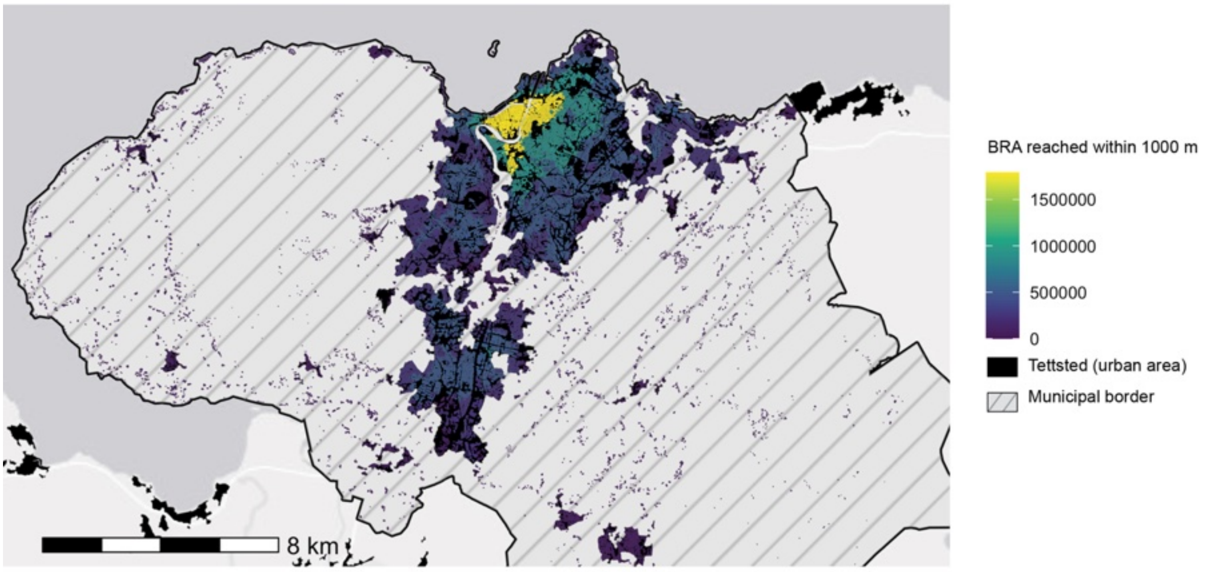

Figure 1. Trondheim's municipal border, tettsteder (urban areas) and floor area density, measured as the total floor area (BRA) reached from buildings within a 1000 m network radius (map source: "ArcGIS Data Appliance," 2022a; Schwalb-Willmann, 2022a).

3.2 Data

We obtained data on walking frequencies from the Norwegian Travel Survey (RVU – Reisevaneundersøkelse), a survey conducted since 1985. Our study is based on the 2018-2019 survey. The survey was designed to be representative of travel activities at the population level on an average day. Data were collected through online forms and phone interviews. In Norway, 88,548 individuals aged 13 years or older responded to the survey. The shares of web and phone responses were 55% and 45%, respectively (Statens Vegvesen, 2019). For Trondheim, the survey comprised data from 3766 individuals. Sociodemographic variables were provided per individual, while address locations were aggregated on small area units (i.e., grunnkrets level). A grunnkrets – hereafter called GK – is a census unit used in Norway for regional statistics. In Trondheim, the sizes range from 0.02 to 18 km2 and 3 to 2986 inhabitants (Trøndelag i Tall, 2023).

3.3 Network Model

The shortest routes and route distances were calculated using detailed axial and segment maps covering the entire city of Trondheim (Manum and Nordstrom, 2013; Rokseth et al., 2019). Axial maps were used for topological measures, and segment maps were used for metric measures. These maps represent all streets, paths, and urban spaces that are accessible to pedestrians. We inspected the networks for missing connections and network errors, and manually corrected errors based on OSM, Google Earth, field visits, and maps and orthophotos provided by Norwegian authorities (Kartverket, 2021).

Besides metric route distance along segments, we included the effect of turns along routes by applying the topological measure "axial steps" as defined by Hillier and Hanson (1984). The axial step is a binary measure: 0 for no turns and 1 for a turn of any angle. Axial steps were applied for integration, reach, and accessible floor area (Section 3.5). Distances through the network were not only used to calculate the shortest routes, but also to set the radii of the calculations to radii corresponding to distances reasonable for walking. The radii applied in this study are as follows:

- Metric: 500 and 1000 m, corresponding to the distances people are typically willing to walk (McCormack et al., 2008). To evaluate the impact of higher accessibility within radii that exceed common single-trip walking distances, 2000 m was applied in addition for reach and weighted reach (Section 3.5).
- Topological: Following previous research findings on topological distances and walking (Hillier, 1996), we applied topological distances of 3, 6, and 9 "axial steps."

Figure 2 shows a comparison between metric and topological distances, visualised as the network distance from Trondheim`s central square.

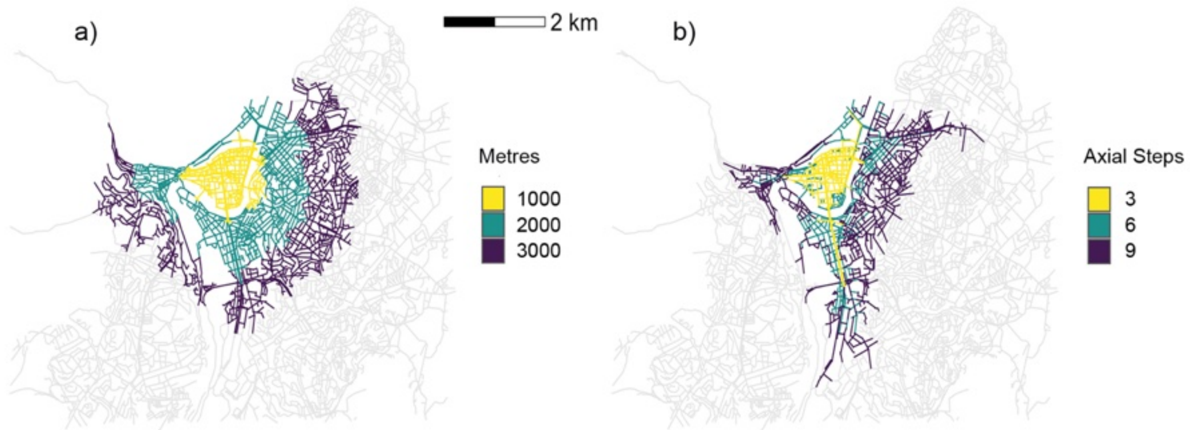

Figure 2. Topologic and metric network radii visualised as a) axial lines coloured by axial steps and b) segment lines coloured by metric distance from Trondheim`s central square.

3.4 Outcome Variable

Our outcome variable was the self-reported walking frequency, obtained by the question, "How often do you walk the whole way to daily destinations during this time of the year?" The answers were:

Never | (2) Rarely | (3) 1-3x/month | (4) 1-2x/week | (5) 3-4x/week | (6) 5x+/week

3.5 Predictor Variables

Reach

We operationalised network connectivity and network density around home locations as reach (Peponis et al., 2008). Reach was calculated in PST (Stavroulaki et al., 2019) as the number of segments or axial lines reached within a given distance from address points within a defined metric or topological network distance through the network (Equation 1 with f(a) = 1).

Weighted Reach

We measured urban density as reach weighted by residents and floor area (Equation 1) — i.e., the number of residents or amount of floor area reached through the network from address points within a certain metric radius (Berghauser Pont et al., 2019). The source of population data is GeoNorge, the Norwegian national online database for cartographic data, where data are aggregated on 250 × 250 m cells (Geonorge, 2023). To disaggregate the data, the number of residents and employees for each cell was evenly distributed over the dwellings and buildings with workplaces in that cell, respectively. For the total floor area per building, we applied "bruksareal," or short "BRA" (Norwegian Building Authority, 2022), for each building, which was provided by the Norwegian Kartverket (Mapping Authority). Here, we included all building types.

$$\mathrm{AR}(o) = \sum_{a \in R_A} f(a) * D(o,a) \tag{1}$$

where A= a set of segments or axial lines within a set radius, f(a) = destination weight, $D(o,a)$ = shortest metric or topological distance from an origin o to an attraction a. For (unweighted) reach, f(a) = 1.

Diversity

Accessible retail diversity accounts for the number of different shop types reached out of the total number of shops reached. We applied a reciprocal Simpson index adapted from Bobkova et al. (2017), where the maximum corresponds to eleven shop types reached within a given distance (Equation 2). The shop types considered were electronics, pharmacies, sports, supermarkets, convenience stores, tea and coffee, mobile phone providers, kitchenware, clothing, shoes, and variety stores (source: Open Street Map - OSM (Boeing, 2021)).

$$DIV_{shops} = \frac{1}{\Sigma \left(\frac{AR\ (shop\ type)}{AR\ (all\ retail\ shops)}\right)^2} \tag{2}$$

where "AR (shop type)" is the number of one shop type reached, and "AR (all retail shops)" is the number of all shops reached.

Similarly, accessible building diversity was calculated as the variety of building types reached within a certain radius (Equation 3). The eight building types were based on the classification by Statistics Norway ("Statistics Norway," 2020).

$$DIV_{buildings} = \frac{1}{\Sigma \left(\frac{AR\ (building\ type)}{AR\ (all\ buildings\ )}\right)^2} \tag{3}$$

Closeness Centrality: Integration

Closeness centrality was measured as topological centrality or "space syntax integration". The integration of an axial line is calculated from the number of lines (N) reached within a set radius of line steps (Figure 2), the mean number of steps to all lines (MD), and the relative asymmetry (RA) (Equations 4 and 5). Note that N in (5) is identical to the topological reach.

$$RA = \frac{2(MD-1)}{N-2} \tag{4}$$

$$Int = \frac{D}{RA} \tag{5}$$

where D normalises integration for systems with different axial line counts (see Stavroulaki et al., 2019, their Equation 3).

Proximity to Destinations

Proximity to destinations was measured as the shortest metric distance through the network from dwellings at georeferenced address points. The following destinations were considered (source: OSM, unless otherwise stated):

- Grocery shops
- Public transport stops
- Leisure areas, e.g., parks, sports facilities, playgrounds
- Local centres: Areas with retail, cafes, and other services/amenities, and often with schools and kindergartens within short walking distances (FramtidsTrondheim, n.d.).
- Centre zones: "areas with at least four different types of commercial activities with city centre functions" (GeoNorge, 2022).
- Campus buildings of the Norwegian University of Science and Technology (GeoNorge, 2021).
- Schools and kindergartens (GeoNorge, 2021).

Area-Based Measures

To compare the performance of "reach" and "weighted reach" with area-based measures of connectivity and density, we further included the number of street segments and residents, as well as the BRA of all buildings per GK area, in the analyses.

3.6 Linking Aggregated and Disaggregated Data

The data used in this study have different spatial units. Reach, attraction reach, and proximity to destinations were calculated from all the address points in Trondheim with PST. Integration values of axial lines were linked to address points via nearest-neighbour joints using GIS. However, the only link between the address points, walking frequencies, and sociodemographic data was the common GK number. Consequently, we used the GK mean values for each predictor variable.

3.7 Sample

For the statistical analyses, we limited the analyses to people aged between 18 and 72 years, corresponding to the minimum age for car driving and upper retirement age in Norway, and to people who reported a) making at least one daily trip per week and b) having no physical limitations to move outdoors. Based on the resulting sample, we further limited the analyses to GKs with at least three participants, resulting in 283 GKs and 2273 participants retained in the analyses. Excluding GKs with fewer than three participants would have removed 42 GKs, so we chose to retain them. The GK characteristics are listed in Table 1.

3.8 Splitting the Dataset

We split the GKs into two groups. We had two reasons for doing so. First, we assumed that the predictor variables impact walking frequencies differently depending on urban density. Second, the initial analyses showed that the statistical assumption of linearity between the predictor variables and the logit of the outcome was frequently violated when all GKs were used. The GKs included in the analyses covered 144 km^2, differing substantially in area (0.02 to 13 km^2), density, and land use (Table 1). We chose a split based on a metric reach (network density) of 2000 m, based on the fewest violations of linearity. The split was based on the median value (1453), resulting in 1136 participants in the high-density GKs and 1137 participants in the low-density GKs. Cooper (2018) used a similar criterion to define a city centre, but with the upper 30% of network links within a 2000 m metric radius. The resulting two groups of GKs are shown in Figure 3 and are, in the following, referred to as high-density GKs and low-density GKs (Figure 3).

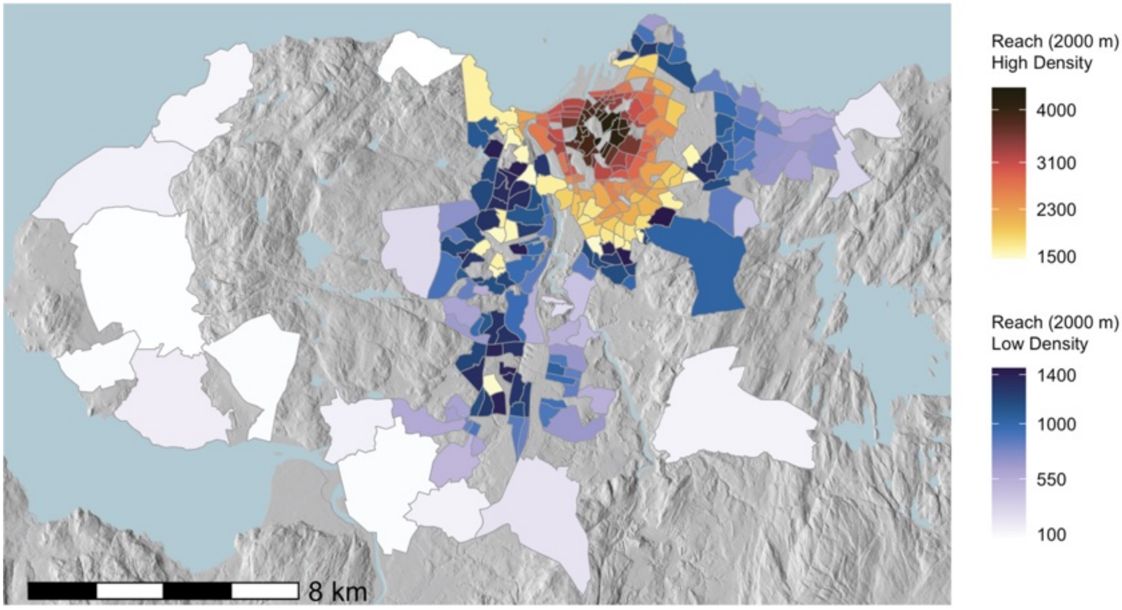

Figure 3. Division of GKs ("grunnkretser") into two groups: a) high-density GKs, coloured red-yellow; b) low-density GKs, coloured white-blue. Colours are based on GK mean values for reach 2000 m. The terrain is shown as shaded relief (DEM source: Kartverket, 2024).

Table 2 shows the share of frequencies reported by RVU participants. The share of people walking frequently (5x+/week) was notably higher (43.5%) in the high-density GKs than in the low-density GKs (22.3%). Correspondingly, the percentage of people walking less frequently was higher in the low-density GKs. The mean walking frequency per GK is shown in Figure 4.

Table 1. GK (grunnkrets) characteristics

	High-density GKs	Low-density GKs	All GKs
Area range (km^2)	0.02 - 1.61	0.05 – 12.8	0.02 – 12.8
Area mean, median, SD	0.13, 0.10, 0.15	0.87, 0.26, 1.90	0.51, 0.17, 1.41
Nr of participants	Number of GKs	Number of GKs	Number of GKs
15 - 32	15	10	25
14 - 10	30	36	66
9-6	37	50	87
5-4	32	31	63
3	26	16	42
Sum	140	143	283

Table 2. Walking frequencies

Walking frequency	High-density GKs	Low-density GKs	All GKs
5-7 times/week	494 (43.5%)	253 (22.3%)	747 (32.9%)
3-4 times/week	196 (17.3%)	201 (17.7%)	397 (17.5%)
1-2 times week	219 (19.3%)	247 (21.7%)	466 (20.5%)
1-3 times/months	83 (7.3%)	121 (10.6%)	204 (9.0%)
Rarely	75 (6.6%)	146 (12.8 %)	221 (9.7%)
Never	69 (6.1%)	169 (14.9%)	238 (10.5%)

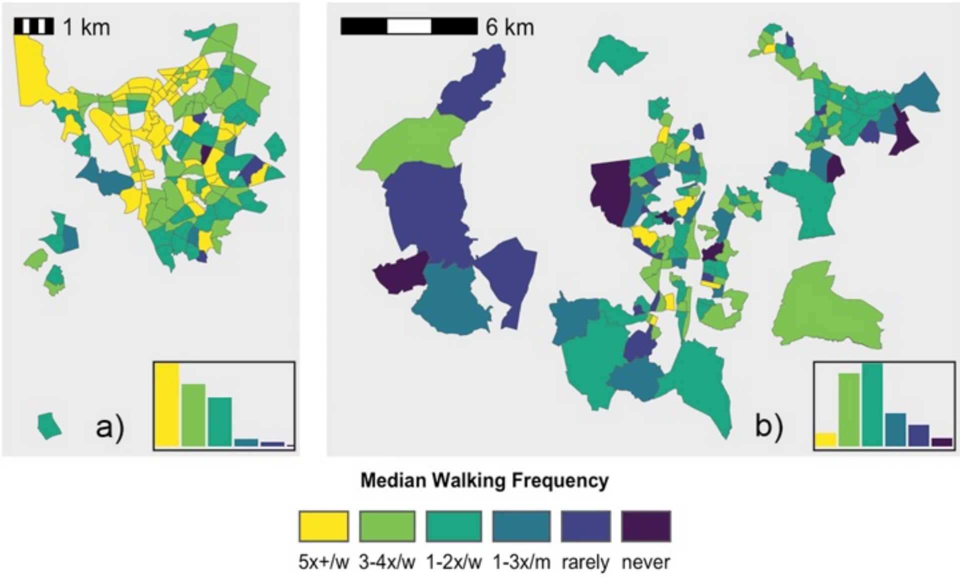

Figure 4. Median walking frequencies per GK for the a) high-density GKs and b) the low-density GKs (map source: GeoNorge, 2024). Boxes show histograms.

3.9 Statistical Analysis

Based on the categorical outcomes, we applied a series of ordinal regressions. We first assessed the impact of reach, weighted reach, integration, and proximity to destinations on walking frequency through bivariate analyses. The second analysis used multivariable models. To determine which predictors yielded the best model fits, we applied a best-subset analysis under AIC optimisation (Zhu et al., 2022). Due to correlations, we did not include reach, accessible BRA, accessible residents, and integration into the same subset selection when their correlation was higher than $r^2 = 0.75$. Instead, we used the variable with the highest bivariate AIC in the first round and then tested subsets with other predictors. The variable yielding the subset with the best final fit was used for the final models. The results of the best subset analyses are presented in Table A2 in the Appendix.

Analyses were adjusted for age, gender, income, and season. Age was categorised as:

18-19 | 20-29 | 35-44 | 45-54 | 55-66 | 67-72.

Income was categorised into nine classes ranging from NOK 10,000 to over NOK 1,000,000 (ca. EUR 870 – 87,000) annually. Seasons were coded as: December – February = winter (1), March – May = spring (2), June – August = summer (3), and September – November = autumn (2). Age, gender, income, and car ownership were not removed from the models, irrespective of significance, whereas season was only retained when increasing the model fit.

We tested the assumption of proportional lines with the Brant test (Brant, 1990) and linearity between the predictor variables and the logit of the outcome variable using the Box-Tidwell test (Royston, 2013). If the assumption of linearity was violated, variables were transformed. In the case of a PLA violation, we applied a partial proportional odds model that frees the affected variables from the PLA constraint. We provide Wald instead of Brant statistics whenever PLA constraints are applied (Williams, 2006). Due to the low number of participants in the 42 GKs, we also conducted sensitivity tests with a minimum of four participants per GK for a) the best subset analyses and b) the multivariable models.

4 Results

4.1 *Unadjusted (Univariate) Ordinal Regression Analysis*

Except for proximity to public transport, accessible building diversity, and segments per GK in the low-density GKs, all predictor variables were positively associated with higher walking frequencies at the $p<0.001$ level (Appendix Table 1). Reach BRA s9 (s9 = 9 axial steps) and reach BRA 1000 m yielded the highest model fit in the high-density GKs, whereas reach BRA 1000 m yielded the highest fit in the low-density GKs.

4.2 *Multivariable Best-Subset Models*

Appendix Table A2 shows the results of the subset selection. In both high- and low-density GKs, the models were limited to fewer than three predictors plus control variables, as models with more predictors were within $AIC\text{-}AIC_{min} \leq 2$, where AIC_{min} was the lowest observed AIC (Burnham and Anderson, 2004). The descriptive statistics for the variables used in the final multivariable models are presented in Table 3.

Table 3. Descriptive statistics for variables used in the multivariable models.

	High-Density GKs (n = 1336)			
	Mean	**Median**	**SD**	**Range**
Reach 2000 m	2651	2545	8181	1460 – 4376
Reach s9	772	741	178	146 - 1493
Reach BRA s9	2,773,667	2400561	1,687,857	159,264 - 5,839,278
Reach BRA 1000 m	673,694	556900	390,979	164,597– 1,625,640
Dist. Grocery	485	467	258	122 – 1349
Age	37.6*	33.0*	14.5*	18 – 72
Car Ownership	Car owner 675 (59%)			Does not own car 461 (41%)
Gender	Female 510 (45%)			Male 626 (55%)

	Low-Density GKs (n = 1337)			
	Mean	**Median**	**SD**	**Range**
Reach 2000 m	909	965	362	62.2 – 1453
Reach s9	241	227	137	28 - 581
Reach BRA s9	515,734	452054	359,930	26,567 – 1,533,996
Reach BRA 1000 m	196,477	203629	94,758	6677 – 401,082
Dist. Grocery	903	712	903	234 - 7553
Age	43.0*	42.0*	14.8*	18 – 72
Car Ownership	Car owner 998 (88%)			Does not own car 139 (12%)
Gender	Female 538 (47%)			Male 599 (53%)

SD = standard deviation. Dist. = distance to; Empl. = employees; s = axial steps.
* based on uncategorised ages

High-Density GKs

In the high-density GKs, the highly correlated ($r^2 = 0.86$) predictors reach BRA s9 and reach BRA 1000 m, in combination with proximity to grocery shops, yielded the best model fits. Model 1 indicates that for each additional 100,000 m^2 of floor area reached within 9 axial steps, the odds for walking increase by a factor of 1.03 (= 3%). Reaching the maximum floor area (5,839,278 m^2) within 9 axial steps instead of the mean (2,773,667 m^2) increased the odds of walking more by a factor of

2.19 (= by 119%). When holding all other variables constant, the results can be expressed as predicted probabilities (marginal effects). The predicted probabilities of walking at the minimum, mean, and maximum values of reach BRA s9 were 28%, 43%, and 62%, respectively.

Model 2 indicates that for each additional 100,000 m^2 of floor area reached within 1000 m, the odds ratios for walking more range from 1.10 to 1.18. For instance, reaching the maximum floor area (1,625,640 m^2) within 1000 m instead of the mean (196,477 m^2) increased the odds of walking 5x or more per week or more (as opposed to less frequently) by a factor of 2.51 (= 151%). The predicted increase in the probability of walking 5x or more per week for Reach BRA 1000 m is similar to Model 1: 31% (min), 43% (mean), and 66% (maximum). A marginal effects plot for Model 2 is shown in Figure 5a, with continuous values of reach BRA 1000 m plotted against different walking frequencies. Reach BRA primarily affected frequent walking ("5x+/week"). The plot for Model 1 shows a similar pattern and is thus omitted.

Reach BRA s9 (Model 1) correlated strongly with reach s9, reach BRA s6, and reach s6 (r^2 = 0.91, 0.88, and 0.88, respectively; see Appendix Figure A2 for a correlation table). Replacing reach BRA s9 with reach BRA s6 or reach s9 yielded AICs of 3354 (+3) and 3357 (+6). Combining these variables with reach 2000 m yielded AICs of 3350 (-1; reach BRA s6) and 3355 (+4; reach s9) (see Appendix Table A3). While an increases in AIC of +4 over Model 1 is significant, models in the ±AIC 4-7 range should not be dismissed (Burnham, 2002).

Low-Density GKs

For the low-density GKs, the best model fit was achieved by reach BRA 1000 m, retail diversity within 1000 m, and building diversity within 500 m. Model 1 indicates that for an additional 100,000 m^2 of floor reached within 1000 m, the odds of walking increase by 3.6%. Reaching the maximum (401,082 m^2) floor area within 1000 m instead of the mean (196,477 m^2) increased the odds of walking by a factor of 1.89 (=89%). A marginal effects plot for the low-density GKs Model 1 is shown in Figure 5b, with continuous values of reach BRA 1000 m plotted against walking frequencies. With increasing reach BRA 1000 m, the probability of walking "5x+/week" and "1-3x month" increased, while the probability of other walking frequencies decreased. Expressed as marginal effects, the predicted probability of walking more than "5x/week" is over twice as high in a GK with maximum reach BRA (34%) than in a GK with minimum reach BRA (13%).

More walking was also associated with walkable access to retail and building diversity. Accessible retail diversity showed a significant association only for walking "1-2/week" or more. Unlike in the high-density GKs, reach correlates only moderately with reach BRA 1000 m ($r^2 \leq 0.65$; Figure A3). Thus, no segment- or axial line-weighted measure achieved a model fit close to reach BRA 1000 m; the closest model fit was achieved with reach s6, with an AIC of 3916 (+8).

Sensitivity Test

The sensitivity test yielded the same subsets. For the high-density GKs, the odds ratios in the multivariable models showed a ≤ 0.5% increase for weighted reach and ≤ 1.5% decrease in proximity to grocery shops. Models 1 and 2 had a larger AIC gap (4, as opposed to 1). In both instances, the best subset favoured Model 1 over Model 2. For the low-density GKs, the odds ratios increased for retail diversity (+13%) and building diversity (+7%).

Table 4. Multivariable Ordinal Models (best subset) for the outcome walking frequencies

High-Density GKs (n = 1136) – Model 1

	OR	COI	P	Wald
Reach BRA s9 (2)	1.03	1.02; 1.03	**<0.001**	0.06
Prox. Grocery (1)	1.07	1.01; 1.13	**0.013**	0.22
Age	0.99	0.91; 1.08	0.83	0.56
Car Ownership	0.86	0.67; 1.11	0.25	0.09
Gender (3)	1.14	0.91; 1.41	0.25	0.61
Income	PLAv	PLAv	**<0.001**-0.72	0.01

AIC: 3351; McFadden Pseudo R^2 = 0.041; Max VIF = 1.64

High-Density GKs (n = 1136) – Model 2

	OR	COI	P	Wald
Reach BRA 1000m (2)	PLAv	PLAv	PLAv	0.02
3-4x/w | 5x+/w	1.12	1.03; 1.22	**0.012**	n.a.
1-2x/w | 3-4x/w	1.16	1.08; 1.24	**<0.001**	n.a.
1-3x/m | 1-2x/w	1.18	1.12; 1.26	**<0.001**	n.a.
rarely | 1-3x/m	1.14	1.09; 1.19	**<0.001**	n.a.
Never | rarely	1.10	1.06; 1.15	**<0.001**	n.a.
Prox. Grocery (1)	1.06	1.00; 1.11	0.062	0.18
Age	0.99	0.91; 1.08	0.85	0.55
Car Ownership	0.87	0.68; 1.13	0.30	0.12
Gender (3)	1.12	0.90; 1.39	0.31	0.58
Income	PLAv	PLAv	**<0.001** - 0.52	0.02

AIC: 3352; McFadden Pseudo R^2 = 0.043; Max VIF = 1.84

Low-Density GK (n = 1137)

	OR	COI	P	Wald
Reach BRA 1000 m (2)	1.36	1.19; 1.57	**<0.001**	0.15
Building Div. 500 m	1.79	1.03; 3.10	**0.039**	0.51
$(\text{Retail Div. 1000 m})^{0.1}$	PLAv	PLAv.	PLAv.	0.001
3-4x/w | 5x+/w	4.59	2.54; 8.28	**<0.001**	n.a.
1-2x/w | 3-4x/w	3.13	1.75; 5.60	**<0.001**	n.a.
1-3x/m | 1-2x/w	2.38	1.32; 4.29	**0.004**	n.a.
rarely | 1-3x/m	1.56	0.83; 2.91	0.17	n.a.
Never | rarely	1.27	0.61; 2.62	0.53	n.a.
Age	1.11	1.02; 1.20	**0.011**	0.24
Car Ownership	0.58	0.42, 0.80	**0.001**	0.13
Gender (3)	1.15	0.93; 1.43	0.20	0.12
Income	0.93	0.88; 0.98	**0.004**	0.75

AIC: 3908; McFadden Pseudo R^2 = 0.030; Max VIF = 1.66

Shown are odds ratios (OR), 95% confidence intervals (COI), significance levels (p), Akaike Information Criterion (AIC), McFadden Pseudo-R^2, results of the Wald proportional lines test, and maximum VIF. P-values in bold font indicate significance at $p < 0.05$. BRA = bruksareal (floor area); Prox. = proximity to the closest; Div. = diversity; PLAv = violation of parallel lines assumption; n.a. = not applicable. Exponents indicate transformations for linearity with the logit of the outcome, and (1) to (3) the units or coding applied: (1) per 100 segments or metres | (2) per 10^5 m^2 | (3) male = 0, female =1.

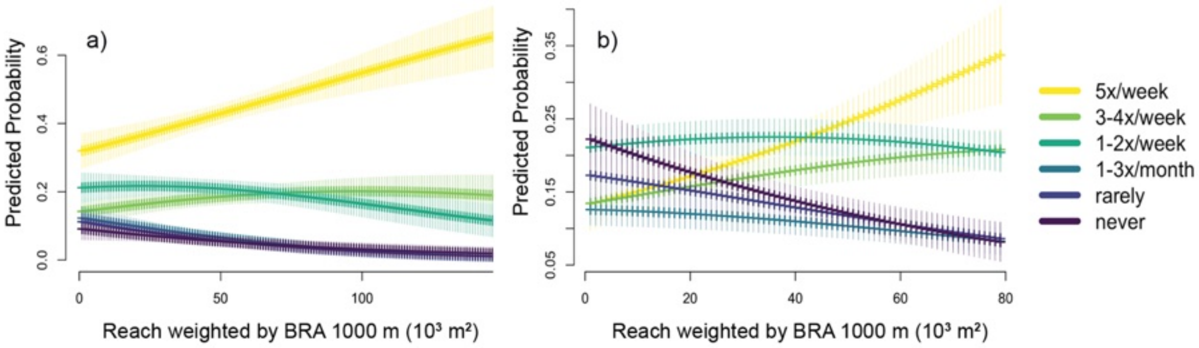

Figure 5. Predicted probabilities walking frequencies for reach weighted by BRA 1000 m for the a) high-density GKs and b) low-density GKs.

5 Discussion

This study investigated the impact of network configurations, network reach, and weighted reach on walking frequency in Trondheim, Norway. We conducted multivariable ordinal regressions, adjusted for proximity to various destinations, sociodemographic variables, and car ownership, and derived final models using best subset analyses. Based on network densities, the research area was divided into low- and high-density "grunnkretser" (GKs; census areas).

Our study is among the first to relate reach and weighted reach to walking frequency. In the multivariable analyses, reach and reach weighted by floor area (bruksareal or "BRA") showed better model fits than integration and area-based measures of connectivity and density. This finding is surprising, given the few studies on reach in the literature. However, several other authors have shown a positive impact of reach on walking to transport stations (Ozbil and Peponis, 2012), walking activity (Ellis et al., 2016) and pedestrian distributions (Pearce et al., 2021; Peponis et al., 2008). Nevertheless, our results revealed notable differences between the high- and low-density GKs.

In the high-density GKs, where walking frequencies are significantly higher than in the low-density GKs, reach weighted by floor area within 9 axial steps and 1000 m were the strongest predictors yielding similar model fits. An equal model fit was achieved by combining reach weighted by floor area within 6 axial steps and reach 2000 m.

Metric reach and weighted reach are closely related to composite walkability indices based on connectivity, density, or pedsheds (Pafka and Dovey, 2017; Frank et al., 2010), but we note high radii (1000 and 2000 m) compared to previous walking studies (e.g., Smith et al., 2017; Villanueva et al., 2012). In contrast, topological reach measured by axial steps is a fundamental departure from traditional walkability metrics, capturing spatial accessibility by minimising turns through the network. A higher topological reach is associated with higher integration (see Equation 4). Highly integrated streets agglomerate buildings, commercial activities, and workplaces (Hillier, 1996), as shown by the high correlation between reach and reach, weighted by floor area within 6 axial steps ($r^2 = 0.93$). Thus, topological reach captures streets with good spatial accessibility to jobs, retail, and other economic activities that shape attractive urban walking environments.

Despite their conceptual differences, the different reach measures tend to be highly correlated, and all capture aspects of network accessibility that matter for walking. While weighting reach by floor area improved the model fits, reach without weighting by land use may serve as a proxy when detailed floor area data are absent. While this confirms previous research that connectivity matters, the relatively high radii (9 axial steps, 1000 – 2000 m) show that the connectivity of pedestrian networks should not only be evaluated within neighbourhoods but also within the wider urban network. Similar findings were reported by Lamíquiz and López-Domínguez (2015), who found integration with 5 axial steps to be a stronger predictor of the decision to walk than 3 steps. Overall, the results for the high-density GKs suggest that frequent walking is encouraged by well-connected networks beyond census area boundaries and proximity to streets with high spatial accessibility.

In the low-density GKs, where walking frequencies are considerably lower than in high-density GKs, the explicit consideration of accessibility to floor area, retail diversity, and building diversity explains — in contrast to the high-density GKs — frequent walking better than only network characteristics. The positive impact of retail diversity on walking can be related to one large shopping mall concentrating most retail, with shops and other amenities providing a possible walking destination. Building diversity near home also encourages walking, as just one additional building type within 500 m increased the odds of walking significantly. In other words, living in a residential area with low accessible floor area density, low retail diversity, and low building type diversity discourages frequent walking, likely due to a lack of attractive destinations within walkable distances.

The different results in the two GK groups relate to the findings by Berghauser Pont and Marcus (2015), who found that the network itself explains pedestrian behaviour in historically grown city centres better than in more newly planned neighbourhoods. While this study focused on pedestrian flows, our results suggest that network configurations also explain walking frequencies in the high-density GKs more than in the low-density GKs. This may be due to the correlations between accessibility and land-use intensity in the denser, older parts of the city. Here, land use patterns could adapt to accessibility advantages or disadvantages over time (Wegener and Fuerst, 2004), with network density proxying the density of attractive walking destinations.

From an urban planning perspective, the results suggest that neither building density nor network density alone are sufficient to promote walking. Instead, it is the balance between network density and land-use density (i.e., buildings, population, and functions) that matters. These correlations are not confined to historic dense city centers. For instance, Schön et al. (2024) found very high correlations between reach and reach weighted by floor area and population in two small towns in Norway with high rates of active travel to school. The rates were significantly impacted by network connectivity and density. While Schön et al.'s (2024) study and the current study are cross-sectional and do not provide causal conclusions, they underline the importance of the network–land use balance. Regression analyses between reach and reach weighted by floor area or population could identify areas with high-density networks that should be prioritised for residential or commercial development (Wang et al., 2019) or areas with insufficient network density relative to building and function density.

Limitations

This study has some limitations. First, due to the available data, the analyses had to be based on travel data aggregated on GKs. Travel data at the address point level would likely improve the analyses, particularly regarding shorter network radii. Second, we also acknowledge that three people per grunnkrets are few, but this number was a compromise between representativeness and retaining an adequate number of GKs. Third, travel data were also self-reported and did not distinguish between utilitarian and recreational walking, while it is known that the impact of urban form differs between walking purposes (Saelens and Handy, 2008). Fourth, the study did not account for residential self-selection, which can confound the association between urban form and travel behaviour (Cao et al., 2009). Finally, given the available data, we could not account for trip length, duration, and destination, or for factors such as slope, sidewalk conditions, and winter maintenance, all of which have been shown to influence pedestrian travel (Fossum and Ryeng, 2022; Saelens and Handy, 2008; Vale et al., 2016).

Conclusions

We conclude that the accessibility of pedestrian networks should be evaluated not only on small scales within neighbourhoods or census areas but also within a wider urban network. Second, living in a denser area supports more walking but not necessarily because of density per se, but also because of land uses that have adapted to well-connected networks and good accessibility over time, a notion supported by the high explanatory power of network reach. Reach is a measure of connectivity, network density, and accessibility, but it is also a proxy for several factors that make walking more attractive, such as alternative route options, a variety of shops and amenities along the way, potentially better-maintained sidewalks, more options to avoid traffic, and overall accessibility to a variety of destinations.

Network topology, as grasped by topological reach, is also important as more integrated streets are favourable for commercial activity and workplaces. In contrast, low-density residential areas discourage frequent walking because of a lack of amenities, services, and retail within walkable distances. While such areas outside the centre cannot provide the dense networks and access to jobs found in centre areas, future urban planning should ensure that areas outside the centre have not only walkable access to retail and grocery but also a variety of building types and functions combined with dense walking networks that provide easy access to functions and attractions.

Finally, the explanatory power of measures applying metric network distances (i.e., reach weighted by floor area 1000 m) is encouraging, as they are easier to implement in practice than topological measures. Nevertheless, network topology also matters because more integrated streets favour the agglomeration of commercial activities and workplaces. To grasp important aspects of topology, topological reach was shown to be as suitable as integration, with reach being easier to communicate and implement in planning.

Data Availability Statement

RVU data are not publicly available because of privacy reasons and access restrictions set by Statens Vegvesen (road authorities). Access to floor area per building (BRA) is restricted by the Norwegian Kartverket (mapping authority). Address points and grunnkretser (census areas) are publicly available at https://kartkatalog.geonorge.no/. The networks used in the analyses are available upon request.

Contributor Statement

Peter Schön wrote the original draft and contributed to visualisation, validation, software, methodology, formal analysis, investigation, and data curation. Eva Heinen and Bendik Manum contributed with review and editing, conceptualisation, methodology, and supervision.

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Conflict of Interest (COI)

There is no conflict of interest.

References

ArcGIS Data Appliance [WWW Document], 2022. World Light Gray Base. URL https://doc.arcgis.com/en/data-appliance/2022/maps/world-light-gray-base.htm (accessed 5.20.23).

Baran, P.K., Rodríed, guez, D.A., Khattak, A.J., 2008. Space syntax and walking in a New Urbanist and suburban neighbourhoods. Journal of Urban Design 13, 5–28. https://doi.org/10.1080/13574800701803498

Berghauser Pont, M., Haupt, P., 2021. Spacematrix. Space, Density and Urban Form. nai010 publishers, Rotterdam.

Berghauser Pont, M., Marcus, L., 2015. What can typology explain that configuration can not?, in: Proceedings of the 10th International Space Syntax Symposium. London, UK. 13-17 July 2015, p. 43:1-43:16.

Berghauser Pont, M., Stavroulaki, G., Marcus, L., 2019. Development of urban types based on network centrality, built density and their impact on pedestrian movement. Environment and Planning B: Urban Analytics and City Science 46, 1549–1564. https://doi.org/10.1177/2399808319852632

Berhie, G.K., Haq, S., 2017. Land use and transport mode choices: Space syntax analysis of American cities. Enquiry (Washington, D.C.) 14, 1–22. https://doi.org/10.17831/enq:arcc.v14i1.429

Bobkova, E., Marcus, L., Pont, M.B., 2017. Multivariable measures of plot systems: Describing the potential link between urban diversity and spatial form based on the spatial capacity concept., in: Proceedings of the 11th International Space Syntax Symposium. Lisbon, Portugal. 3–7 July 2017, p. 47.1-47.15.

Boeing, G., 2021. Street network models and indicators for every urban area in the world. Geographical Analysis 54, 519–535. https://doi.org/10.1111/gean.12281

Bolin, D., Verendel, V., Berghauser Pont, M., Stavroulaki, I., Ivarsson, O., Håkansson, E., 2021. Functional ANOVA modelling of pedestrian counts on streets in three European cities. Journal of the Royal Statistical Society. Series A: Statistics in Society. https://doi.org/10.1111/rssa.12646

Brant, R., 1990. Assessing proportionality in the proportional odds model for ordinal logistic regression. Biometrics 46, 1171–1178. https://doi.org/10.2307/2532457

Burnham, K.P., 2002. Information and likelihood theory: a basis for model selection and inference. Model selection and multimodel inference: a practical information-theoretic approach 49–97.

Burnham, K.P., Anderson, D.R., 2004. Multimodel inference: Understanding AIC and BIC in model selection. Sociol. Methods Res. 33, 261–304. https://doi.org/10.1177/0049124104268644

Cao, X. (Jason), Mokhtarian, P.L., Handy, S.L., 2009. Examining the impacts of residential self-selection on travel behaviour: A focus on empirical findings. Transport Reviews 29, 359–395. https://doi.org/10.1080/01441640802539195

Chiaradia, A., Cooper, C.H., Wedderburn, M., 2014. Network Geography and Accessibility, in: Proceedings of the 12th Transport Practitioners' Meeting. London: PTRC.

Chiaradia, A., Hillier, B., Schwander, C., Wedderburn, M., 2012. Compositional and urban form effects on centres in Greater London. Proceedings of the Institution of Civil Engineers: Urban Design and Planning 165, 21–42. https://doi.org/10.1680/udap.2012.165.1.21

Cooper, C.H.V., 2018. Predictive spatial network analysis for high-resolution transport modeling, applied to cyclist flows, mode choice, and targeting investment. International Journal of Sustainable Transportation 12, 714–724. https://doi.org/10.1080/15568318.2018.1432730

Cooper, C.H.V., 2017. Using spatial network analysis to model pedal cycle flows, risk and mode choice. Journal of Transport Geography 58, 157–165. https://doi.org/10.1016/j.jtrangeo.2016.12.003

Cooper, C.H.V., Chiaradia, A.J.F., 2020. sDNA: 3-d spatial network analysis for GIS, CAD, Command Line & Python. SoftwareX 12. https://doi.org/10.1016/j.softx.2020.100525

Cooper, C.H.V., Harvey, I., Orford, S., Chiaradia, A.J.F., 2021. Using multiple hybrid spatial design network analysis to predict longitudinal effect of a major city centre redevelopment on pedestrian flows. Transportation 48, 643–672. https://doi.org/10.1007/s11116-019-10072-0

De Nazelle, A., Nieuwenhuijsen, M.J., Antó, J.M., Brauer, M., Briggs, D., Braun-Fahrlander, C., Cavill, N., Cooper, A.R., Desqueyroux, H., Fruin, S., 2011. Improving health through policies that promote active travel: a review of evidence to support integrated health impact assessment. Environment International 37, 766–777.

Dovey, K., Pafka, E., 2020. What is walkability? The urban DMA. Urban Studies 57, 93–108. https://doi.org/10.1177/0042098018819727

Ellis, G., Hunter, R., Tully, M.A., Donnelly, M., Kelleher, L., Kee, F., 2016. Connectivity and physical activity: using footpath networks to measure the walkability of built environments. Environment and Planning B: Planning and Design 43, 130–151. https://doi.org/10.1177/0265813515610672

Feng, C., Zhang, W., 2019. Algorithms for the parametric analysis of metric, directional, and intersection reach. Environment and Planning B: Urban Analytics and City Science 46, 1422–1438. https://doi.org/10.1177/2399808319827299

Fonseca, F., Ribeiro, P.J.G., Conticelli, E., Jabbari, M., Papageorgiou, G., Tondelli, S., Ramos, R.A.R., 2022. Built environment attributes and their influence on walkability. International Journal of Sustainable Transportation 16, 660–679. https://doi.org/10.1080/15568318.2021.1914793

Fossum, M., Ryeng, E.O., 2022. Pedestrians' and bicyclists' route choice during winter conditions. Urban, Planning and Transport Research 10, 38–57. https://doi.org/10.1080/21650020.2022.2034524

FramtidsTrondheim [WWW Document], n.d. URL https://sites.google.com/trondheim.kommune.no/framtidstrondheim/lokale-sentra (accessed 6.20.22).

Frank, L.D., Sallis, J.F., Saelens, B.E., Leary, L., Cain, K., Conway, T.L., Hess, P.M., 2010. The development of a walkability index: application to the Neighborhood Quality of Life Study. British Journal of Sports Medicine 44, 924–933. https://doi.org/10.1136/bjsm.2009.058701

GeoNorge [WWW Document], 2024. Statistiske enheter grunnkretser - Kartkatalogen. URL https://kartkatalog.geonorge.no/metadata/statistiske-enheter-grunnkretser/51d279f8-e2be-4f5e-9f72-1a53f7535ec1 (accessed 12.2.24).

Geonorge [WWW Document], 2023. Befolkning på rutenett 250 m. URL https://kartkatalog.geonorge.no/metadata/befolkning-paa-rutenett-250-m/ (accessed 3.17.23).

GeoNorge [WWW Document], 2022. Geonorge. URL https://kartkatalog.geonorge.no/metadata/sentrumssoner/55b401f3-2ea1-4045-9f87-22ac9d6ecf66 (accessed 6.3.22).

GeoNorge [WWW Document], 2021. FKB-Bygning - Kartkatalogen. URL https://kartkatalog.geonorge.no/metadata/fkb-bygning/8b4304ea-4fb0-479c-a24d-fa225e2c6e97?search=byggnu (accessed 12.2.24).

Gössling, S., Choi, A., Dekker, K., Metzler, D., 2019. The social cost of automobility, cycling and walking in the european union. Ecological Economics 158, 65–74. https://doi.org/10.1016/j.ecolecon.2018.12.016

Grue, B., Landa-Mata, I., Langset Flotve, B., 2021. Den nasjonale reisevaneundersøkelsen 2018/19-nøkkelrapport. Oslo: TØI 198.

Hall, C.M., Ram, Y., 2018. Walk score® and its potential contribution to the study of active transport and walkability: A critical and systematic review. Transportation Research Part D: Transport and Environment 61, 310–324. https://doi.org/10.1016/j.trd.2017.12.018

Hillier, B., 1996. Cities as movement economies. Urban design international 1, 41–60. https://doi.org/10.1057/udi.1996.5

Hillier, B., Hanson, J., 1984. The Social Logic of Space. Cambridge University Press.

Hillier, B., Iida, S., 2005. Network and psychological effects in urban movement, International Conference on Spatial Information Theory, COSIT 2005. Lecture Notes in Computer Science. Springer, Ellicottville, NY.

Jacobs, J., 1961. The death and life of great American cities. Random House.

Kang, C., 2018. The S+5Ds: Spatial access to pedestrian environments and walking in Seoul, Korea. CITIES 77, 130–141. https://doi.org/10.1016/j.cities.2018.01.019

Kartverket [WWW Document], 2024. Høydedata. URL https://hoydedata.no/LaserInnsyn2/ (accessed 8.3.24).

Kartverket [WWW Document], 2021. Kartverket, Flyfoto. URL https://www.kartverket.no/til-lands/flyfoto (accessed 9.24.22).

Knapskog, M., Peters, S., 2021. Characteristics of walking strategies affecting their usefulness and effect: Studies of walking strategies in Haugesund, Trondheim, and Ås (No. TØI rapport 1839/2021, 8248023729).

Knight, P.L., Marshall, W.E., 2015. The metrics of street network connectivity: their inconsistencies. Journal of Urbanism 8, 241–259. https://doi.org/10.1080/17549175.2014.909515

Koohsari, M., Owen, N., Cerin, E., Giles-Corti, B., Sugiyama, T., 2016. Walkability and walking for transport: characterizing the built environment using space syntax. International Journal of Behavioral Nutrition and Physical Activity 13. https://doi.org/10.1186/s12966-016-0448-9

Koohsari, M.J., Sugiyama, T., Lamb, K.E., Villanueva, K., Owen, N., 2014. Street connectivity and walking for transport: Role of neighborhood destinations. Preventive Medicine 66, 118–122. https://doi.org/10.1016/j.ypmed.2014.06.019

Lahoorpoor, B., Levinson, D.M., 2020. Catchment if you can: The effect of station entrance and exit locations on accessibility. Journal of Transport Geography 82, 102556.

Lamíquiz, P.J., López-Domínguez, J., 2015. Effects of built environment on walking at the neighbourhood scale. A new role for street networks by modelling their configurational accessibility? Transportation Research Part A: Policy and Practice 74, 148–163. https://doi.org/10.1016/j.tra.2015.02.003

Lee, I.-M., Buchner, D.M., 2008. The importance of walking to public health. Medicine and Science in Sports and Exercise 40, S512–S518. https://doi.org/10.1249/MSS.0b013e31817c65d0

Legeby, A., Koch, D., Abshirini, E., 2017. Characterizing urban centres: Reading configuration as point, line, field, in: Proceedings of the 11th International Space Syntax Symposium. Presented at the 11th International Space Syntax Symposium, Lisbon, Portugal. 3–7 July 2017, p. 78:1-78.16.

Manum, B., Nordstrom, T., 2013. Integrating bicycle network analysis in urban design: Improving bikeability in Trondheim by combining space syntax and GIS-methods using the place syntax tool., in: Proceedings of the 9th International Space Syntax Symposium. Seoul, South Korea. 31 Oct – 3 Nov 2013, pp. 1–14.

Marcus, L., Pont, M.B., Bobkova, E., 2017. Cities as accessible densities and diversities - Adding attraction variables to configurational analysis, in: Proceedings of the 11th International Space Syntax Symposium. Lisbon, Portugal. 3–7 July 2017, p. 167.1-167.12.

McCormack, G.R., Cerin, E., Leslie, E., du Toit, L., Owen, N., 2008. Objective versus perceived walking distances to destinations: Correspondence and predictive validity. Environment and Behavior 40, 401–425. https://doi.org/10.1177/0013916507300560

Netto, V.M., Saboya, R., Vargas, J.C., Figueiredo, L., Freitas, C., Pinheiro, M., 2012. The convergence of patterns in the city: (Isolating) the effects of architectural morphology on movement and activity, in: Proceedings of the 8th International Space Syntax Symposium. Presented at the Santiago, Chile. 3-6 Jan 2012, p. 8167:1-8167:32.

Norwegian Building Authority [WWW Document], 2022. URL https://dibk.no/verktoy-og-veivisere/andre-fagomrader/hvor-stort-kan-du-bygge/hvor-stort-kan-du-bygge/dette-er-bruksareal-t-bra/ (accessed 6.3.22).

Ozbil, A., Peponis, J., 2012. The effects of urban form on walking to transit, in: Proceedings of the 8th International Space Syntax Symposium. Santiago, Chile. 3-6 Jan 2012, p. 8030:1-8030:15.

Ozbil, A., Yesiltepe, D., Argin, G., Rybarczyk, G., 2021. Children's active school travel: Examining the combined perceived and objective built-environment factors from space syntax. International Journal of Environmental Research and Public Health 18, 1–22. https://doi.org/10.3390/ijerph18010286

Pafka, E., Dovey, K., 2017. Walkable access, in: Mapping Urbanities: Morphologies, Flows, Possibilities. pp. 41–61. https://doi.org/10.4324/9781315309170

Pearce, D.M., Matsunaka, R., Oba, T., Yamamoto, S., 2021. Utilising dedicated pedestrian networks to understand the relationship between accessibility and pedestrian density in Asian cities. International Journal of Transport Development and Integration 5, 150–161. https://doi.org/10.2495/TDI-V5-N2-150-161

Peponis, J., Bafna, S., Zhang, Z., 2008. The connectivity of streets: reach and directional distance. Environment and Planning B: Planning and Design 35, 881–901. https://doi.org/10.1068/b33088

Porta, S., Crucitti, P., Latora, V., 2006. The network analysis of urban streets: a primal approach. Environment and Planning B: Planning and Design 33, 705–725. https://doi.org/10.1068/b32045

Rokseth, L.S., B. Manum, Nordström, T., 2019. Assessing cities: Applying GIS-based methods for mapping cross-scale spatial indicators, in: IOP Conference Series: Earth and Environmental Science. p. 012055. https://doi.org/10.1088/1755-1315/352/1/012055

Royston, P., 2013. Boxtid: Stata module to fit Box-Tidwell and exponential regression models.

Saelens, B.E., Handy, S.L., 2008. Built environment correlates of walking: a review. Medicine and Science in Sports and Exercise 40, S550.

Salvo, G., Lashewicz, B.M., Doyle-Baker, P.K., McCormack, G.R., 2018. Neighbourhood built environment influences on physical activity among adults: A systematized review of qualitative evidence. Int. J. Environ. Res. Public Health 15. https://doi.org/10.3390/ijerph15050897

Sarkar, C., Webster, C., Gallacher, J., 2018. Neighbourhood walkability and incidence of hypertension: Findings from the study of 429,334 UK Biobank participants. International Journal of Hygiene and Environmental Health 221, 458–468. https://doi.org/10.1016/j.ijheh.2018.01.009

Schlossberg, M., Greene, J., Phillips, P.P., Johnson, B., Parker, B., 2006. School trips: Effects of urban form and distance on travel mode. Journal of the American Planning Association 72, 337–346. https://doi.org/10.1080/01944360608976755

Schön, P., Heinen, E., Rangul, V., Sund, E.R., Manum, B., 2024. The impact of street network connectivity on active school travel: Norway's HUNT study. Environment and Planning B: Urban Analytics and City Science 51. https://doi.org/10.1177/23998083241235978

Schwalb-Willmann, J., 2022. basemaps: A lightweight package to access spatial basemaps from open sources such as "OpenStreetMap", "Carto", "Mapbox" and others in R.

Scoppa, M.D., Peponis, J., 2015. Distributed attraction: The effects of street network connectivity upon the distribution of retail frontage in the city of Buenos Aires. Environment and Planning B: Planning and Design 42, 354–378. https://doi.org/10.1068/b130051p

Sevtsuk, A., Mekonnen, M., 2012. Urban network analysis. A new toolbox for ArcGIS. Revue internationale de géomatique 22, 287–305. https://doi.org/10.3166/rig.22.287-305

Sharmin, S., Kamruzzaman, M., 2018. Meta-analysis of the relationships between space syntax measures and pedestrian movement. Transport Reviews 38, 524–550. https://doi.org/10.1080/01441647.2017.1365101

Shields, R., Gomes da Silva, E.J., Lima e Lima, T., Osorio, N., 2021. Walkability: a review of trends. Journal of Urbanism. https://doi.org/10.1080/17549175.2021.1936601

Smith, M., Hosking, J., Woodward, A., Witten, K., MacMillan, A., Field, A., Baas, P., Mackie, H., 2017. Systematic literature review of built environment effects on physical activity and active transport - an update and new findings on health equity. International Journal of Behavioral Nutrition and Physical Activity 14. https://doi.org/10.1186/s12966-017-0613-9

Ståhle, A., 2008. Compact sprawl: Exploring public open space and contradictions in urban density. KTH, School of Architecture and the Built Environment (ABE), Architecture.

Ståhle, A., Marcus, L., Karlström, A., Koch, D., 2010. Place syntax—geographic accessibility with axial lines. Environment and Planning, B: Planning and Design.

Statens Vegvesen [WWW Document], 2019. Den nasjonale reisevaneundersøkelsen 2018/2019. URL https://www.vegvesen.no/fag/fokusomrader/nasjonal-transportplan/den-nasjonale-reisevaneundersokelsen/reisevaner-2019/ (accessed 6.20.22).

Statistics Norway, 2002. Tettsted [WWW Document]. Variabeldefinisjon Tettsted. URL https://www.ssb.no/a/metadata/conceptvariable/vardok/141/nb (accessed 7.14.24).

Statistics Norway [WWW Document], 2020. Classification of type of building /cadastre. URL https://www.ssb.no/en/klass/klassifikasjoner/31 (accessed 6.13.22).

Stavroulaki, G., Koch, D., Legeby, A., Marcus, L., Ståhle, A., Berghauser Pont, M., 2019. Documentation PST 20191122. https://doi.org/10.13140/RG.2.2.25718.55364

Trøndelag i Tall [WWW Document], 2023. Befolkning i delområder og grunnkretser | Trøndelag i tall. URL https://trondelagitall.no/statistikk/befolkning-i-delomrader-og-grunnkretser (accessed 4.24.23).
Trondheim kommune [WWW Document], 2022. Trondheim kommune. URL https://www.trondheim.kommune.no/aktuelt/om-kommunen/statistikk/befolkningsstatistikk/ (accessed 6.20.22).
Turner, A., 2007. From axial to road-centre lines: a new representation for space syntax and a new model of route choice for transport network analysis. Environment and Planning B: Planning and Design 34, 539–555.
Vale, D.S., Saraiva, M., Pereira, M., 2016. Active accessibility: A review of operational measures of walking and cycling accessibility. Journal of Transport and Land Use 9, 209–235. https://doi.org/10.5198/jtlu.2015.593
Villanueva, K., Giles-Corti, B., Bulsara, M., McCormack, G.R., Timperio, A., Middleton, N., Beesley, B., Trapp, G., 2012. How far do children travel from their homes? Exploring children's activity spaces in their neighborhood. Health and Place 18, 263–273. https://doi.org/10.1016/j.healthplace.2011.09.019
Wang, Z., Han, Q., de Vries, B., 2019. Land use/Land cover and accessibility: Implications of the correlations for land use and transport planning. Applied Spatial Analysis and Policy 12, 923–940. https://doi.org/10.1007/s12061-018-9278-2
Wegener, M., Fuerst, F., 2004. Land-Use Transport Interaction: State of the Art. University Library of Munich, Germany.
Williams, R., 2006. Generalized ordered logit/partial proportional odds models for ordinal dependent variables. Stata J. 6, 58–82. https://doi.org/10.1177/1536867x0600600104
Zhu, J., Wang, X., Hu, L., Huang, J., Jiang, K., Zhang, Y., Lin, S., Zhu, J., 2022. abess: A fast best-subset selection library in Python and R. Journal of Machine Learning Research 23, 1–7.

Appendix A

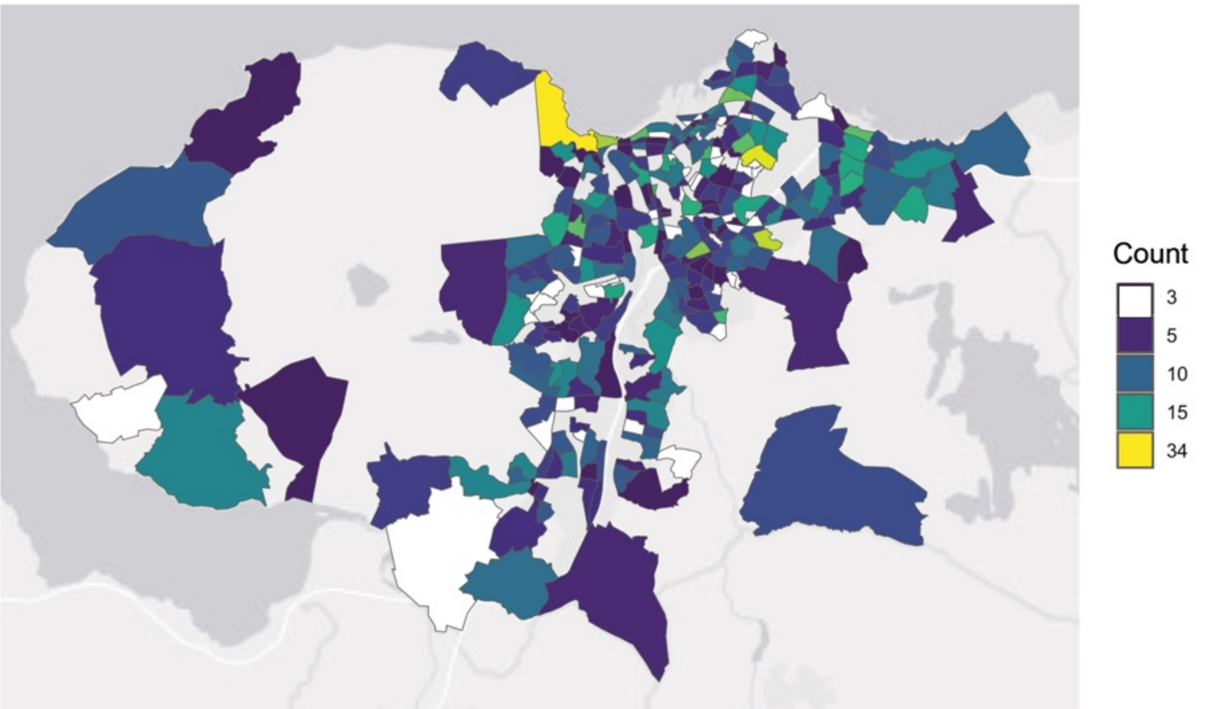


Figure A1: Count of participants included in the analysis per GK (map sources: ArcGIS Data Appliance, 2022; GeoNorge, 2024; Schwalb-Willmann, 2022).

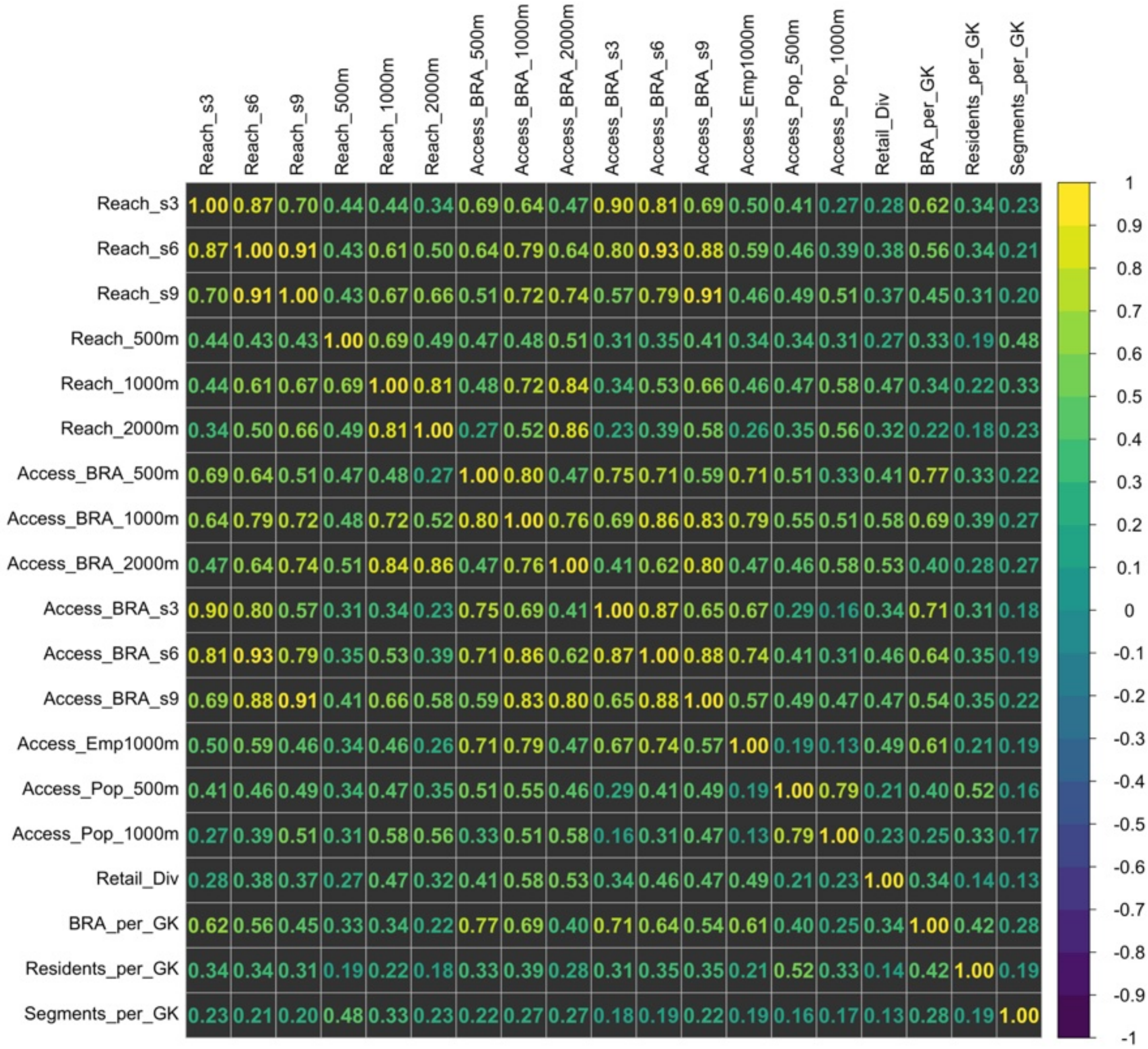
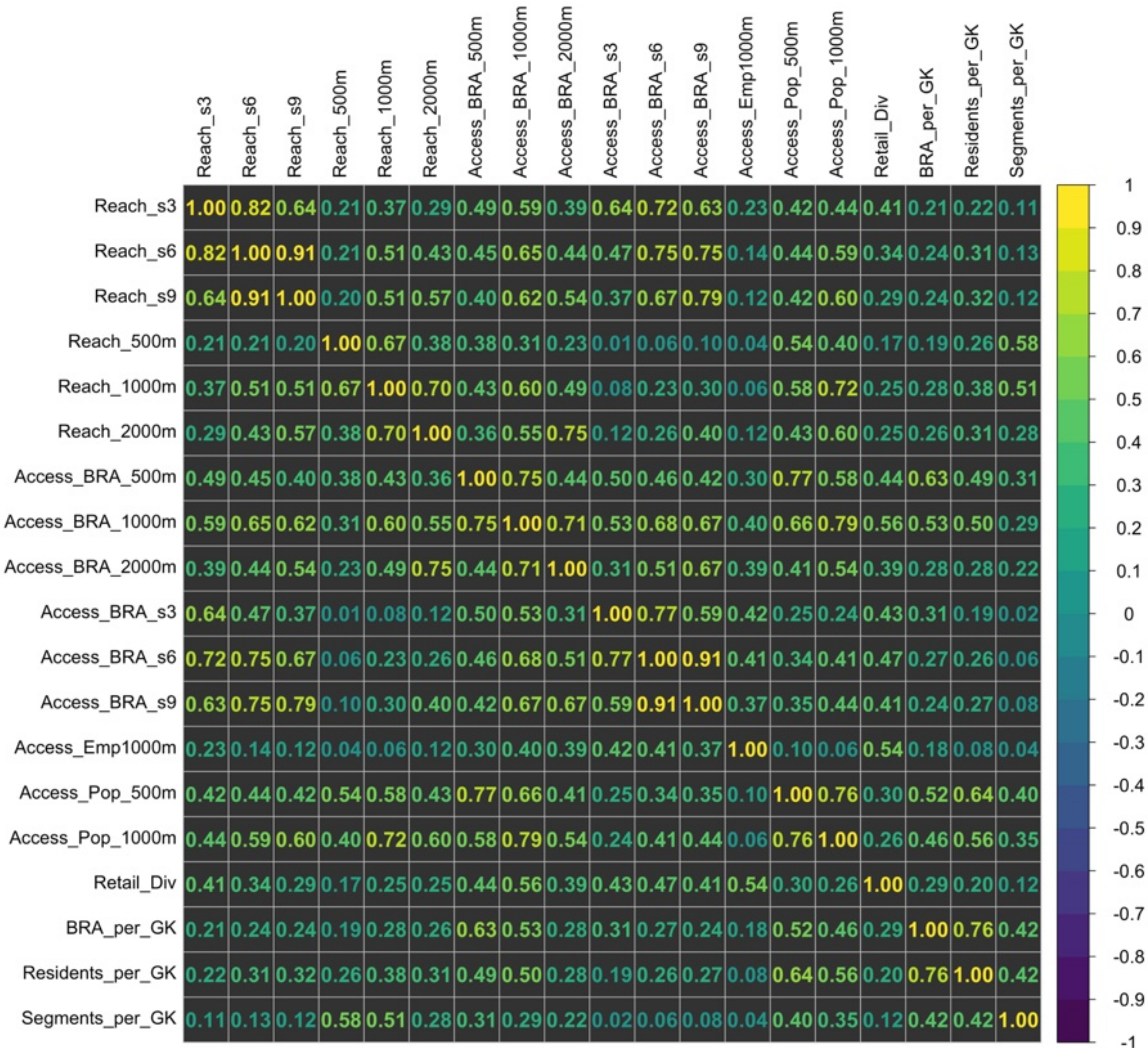


Figure A2: Correlation table for the high-density GKs. All values are given as r^2.



	Reach_s3	Reach_s6	Reach_s9	Reach_500m	Reach_1000m	Reach_2000m	Access_BRA_500m	Access_BRA_1000m	Access_BRA_2000m	Access_BRA_s3	Access_BRA_s6	Access_BRA_s9	Access_Emp1000m	Access_Pop_500m	Access_Pop_1000m	Retail_Div	BRA_per_GK	Residents_per_GK	Segments_per_GK
Reach_s3	1.00	0.82	0.64	0.21	0.37	0.29	0.49	0.59	0.39	0.64	0.72	0.63	0.23	0.42	0.44	0.41	0.21	0.22	0.11
Reach_s6	0.82	1.00	0.91	0.21	0.51	0.43	0.45	0.65	0.44	0.47	0.75	0.75	0.14	0.44	0.59	0.34	0.24	0.31	0.13
Reach_s9	0.64	0.91	1.00	0.20	0.51	0.57	0.40	0.62	0.54	0.37	0.67	0.79	0.12	0.42	0.60	0.29	0.24	0.32	0.12
Reach_500m	0.21	0.21	0.20	1.00	0.67	0.38	0.38	0.31	0.23	0.01	0.06	0.10	0.04	0.54	0.40	0.17	0.19	0.26	0.58
Reach_1000m	0.37	0.51	0.51	0.67	1.00	0.70	0.43	0.60	0.49	0.08	0.23	0.30	0.06	0.58	0.72	0.25	0.28	0.38	0.51
Reach_2000m	0.29	0.43	0.57	0.38	0.70	1.00	0.36	0.55	0.75	0.12	0.26	0.40	0.12	0.43	0.60	0.25	0.26	0.31	0.28
Access_BRA_500m	0.49	0.45	0.40	0.38	0.43	0.36	1.00	0.75	0.44	0.50	0.46	0.42	0.30	0.77	0.58	0.44	0.63	0.49	0.31
Access_BRA_1000m	0.59	0.65	0.62	0.31	0.60	0.55	0.75	1.00	0.71	0.53	0.68	0.67	0.40	0.66	0.79	0.56	0.53	0.50	0.29
Access_BRA_2000m	0.39	0.44	0.54	0.23	0.49	0.75	0.44	0.71	1.00	0.31	0.51	0.67	0.39	0.41	0.54	0.39	0.28	0.28	0.22
Access_BRA_s3	0.64	0.47	0.37	0.01	0.08	0.12	0.50	0.53	0.31	1.00	0.77	0.59	0.42	0.25	0.24	0.43	0.31	0.19	0.02
Access_BRA_s6	0.72	0.75	0.67	0.06	0.23	0.26	0.46	0.68	0.51	0.77	1.00	0.91	0.41	0.34	0.41	0.47	0.27	0.26	0.06
Access_BRA_s9	0.63	0.75	0.79	0.10	0.30	0.40	0.42	0.67	0.67	0.59	0.91	1.00	0.37	0.35	0.44	0.41	0.24	0.27	0.08
Access_Emp1000m	0.23	0.14	0.12	0.04	0.06	0.12	0.30	0.40	0.39	0.42	0.41	0.37	1.00	0.10	0.06	0.54	0.18	0.08	0.04
Access_Pop_500m	0.42	0.44	0.42	0.54	0.58	0.43	0.77	0.66	0.41	0.25	0.34	0.35	0.10	1.00	0.76	0.30	0.52	0.64	0.40
Access_Pop_1000m	0.44	0.59	0.60	0.40	0.72	0.60	0.58	0.79	0.54	0.24	0.41	0.44	0.06	0.76	1.00	0.26	0.46	0.56	0.35
Retail_Div	0.41	0.34	0.29	0.17	0.25	0.25	0.44	0.56	0.39	0.43	0.47	0.41	0.54	0.30	0.26	1.00	0.29	0.20	0.12
BRA_per_GK	0.21	0.24	0.24	0.19	0.28	0.26	0.63	0.53	0.28	0.31	0.27	0.24	0.18	0.52	0.46	0.29	1.00	0.76	0.42
Residents_per_GK	0.22	0.31	0.32	0.26	0.38	0.31	0.49	0.50	0.28	0.19	0.26	0.27	0.08	0.64	0.56	0.20	0.76	1.00	0.42
Segments_per_GK	0.11	0.13	0.12	0.58	0.51	0.28	0.31	0.29	0.22	0.02	0.06	0.08	0.04	0.40	0.35	0.12	0.42	0.42	1.00

Figure A3: Correlation table for the low-density GKs. All values are given as r^2.

Table A1. Univariate ordinal regression results

	High-Density GK (n=1136)							Low-Density GK (n=1137)						
Reach (1)	P	Range	OR	COI	AIC	Brant	Boxtid	P	Range	OR	COI	AIC	Brant	Boxtid
3 Axial Steps	***	[1.5-17]	1.13	1.10; 1.17	3407	0.04	0.01	***	[0.8-4.9]	1.49	1.30; 1.70	3975	0.04	0.12
500 m	***	[6.4-45]	1.04	1.03; 1.06	3434	0.02	0.04	***	[1.1-24]	1.07	1.03; 1.10	3993	0.05	0.31
Reach (2)														
6 Axial Steps	***	[0.6-7.3]	1.33	1.26; 1.42	3385	0.03	0.93	***	[0.2-2.6]	1.91	1.57; 2.34	3969	0.06	0.04
9 Axial Steps	***	[1.5-15]	1.15	1.11; 1.19	3390	0.03	0.17	***	[0.3-5.8]	1.28	1.18; 1.38	3969	0.06	0.09
1000 m	***	[3.7-13]	1.16	1.11; 1.23	3425	0.01	0.64	***	[0.3-8.4]	1.25	1.16; 1.35	3973	0.03	0.19
2000 m	***	[15-44]	1.06	1.04; 1.07	3402	0.03	0.07	***	[0.6-15]	1.09	1.06; 1.12	3977	0.05	0.44
Reach Residents (2)														
500 m	***	[3.5-48]	1.04	1.03; 1.06	3423	0.0	0.15	***	[0.1-13]	1.13	1.09; 1.17	3968	0.11	0.04
1000 m	***	[21-126]	1.01	1.10; 1.02	3424	0.01	0.55	***	[0.4-51]	1.03	1.02; 1.04	3958	0.11	0.14
Reach Employees (2)														
500 m	***	[0.1-126]	1.02	1.01; 1.02	3439	0.02	0.00	***	[0.0-7.3]	1.20	1.1; 1.30	3990	0.05	0.00
1000 m	***	[2.9-253]	1.01	1.91; 1.01	3394	0.00	0.00	***	[0.0-1.8]	1.04	1.02; 1.06	3987	0.05	0.00
Reach BRA (3)														
3 Axial Steps	***	[0.1-12]	1.17	1.13; 1.21	3397	0.05	0.00	***	[0.0-2.6]	2.05	1.61; 2.60	3972	0.01	0.00
6 Axial Steps	***	[0.5-35]	1.05	1.04; 1.06	3372	0.02	0.25	***	[0.2-7.6]	1.22	1.15; 1.30	3968	0.04	0.00
9 Axial Steps	***	[1.6-58]	1.03	1.03; 1.04	3369	0.03	0.17	***	[0.2-15]	1.10	1.07; 1.13	3967	0.08	0.03
500 m	***	[0.3-6.6]	1.47	1.33; 1.62	3405	0.01	0.00	***	[0.0-1.0]	6.34	3.84; 10.4	3956	0.05	0.02
1000 m	***	[1.6-16]	1.16	1.12; 1.19	3371	0.00	0.03	***	[0.1-4.0]	1.59	1.42; 1.79	3942	0.04	0.30
2000 m	***	[10-47]	1.05	1.04; 1.06	3380	0.02	0.97	***	[0.3-15]	1.10	1.07; 1.14	3966	0.05	0.32
Reach Retail Diversity														
1000 m	***	[0.0-7.1]	1.32	1.23; 1.42	3412	0.03	0.06	***	[0.0–6.1]	1.35	1.23; 1.48	3965	0.02	0.00
Reach Build. Diversity														
500 m	***	[1.0-3.1]	1.76	1.31; 2.36	3458	0.14	0.00	n.s.	[1.0-2.2]	1.24	0.73; 2.12	4008	0.00	0.31
1000 m	***	[1.0-2.8]	2.15	1.57, 2.94	3448	0.17	0.00	n.s.	[1.0-2.1]	0.93	0.53; 1.61	4009	0.00	0.45
Integration														
3 Axial Steps	***	[1.1-3.1]	2.79	2.18; 3.57	3403	0.06	0.95	***	[0.8-2.0]	3.59	2.35; 5.470	3973	0.14	0.85
6 Axial Steps	***	[0.9-2.0]	6.37	4.16; 9.74	3397	0.07	0.45	***	[0.7-1.4]	7.76	4.14; 14.6	3970	0.14	0.71
9 Axial Steps	***	[0.8-1.5]	16.41	8.88; 30.4	3390	0.04	0.11	***	[0.5-1.2]	14.3	6.51; 31.4	3973	0.04	0.77
Area-based														
Segments/GK (2)	***	[1.5-19]	1.08	1.05; 1.13	3454	0.09	0.15	*	[0.1–8.7]	1.09	1.02; 1.17	4003	0.03	0.00
Residents/GK (2)	***	[3.1-227]	1.01	1.01; 1.01	3416	0.02	0.18	***	[4.3–37]	1.04	1.03; 1.05	3975	0.29	0.04
BRA/GK (3)	***	[1.0-20]	1.12	1.09; 1.05	3412	0.10	0.14	***	[0.0–5.3]	1.30	1.19; 1.41	3972	0.04	0.05
Proximity to (2)														
Grocery Shop	***	[1.2-14]	1.20	1.15; 1.25	3398	0.18	0.14	***	[2.3-76]	1.04	1.03; 1.06	3978	0.05	0.00
Public Transport	***	[0.4-27]	1.22	1.11; 1.35	3456	0.82	0.00	**	[1.3-12]	1.11	1.03; 1.19	4002	0.18	0.02
Leisure Areas	***	[0.4.6.3]	1.37	1.25; 1.50	3427	0.28	0.12	***	[0.4-6.3]	1.07	1.03; 1.11	3997	0.07	0.72
Center Zones	***	[0.0-34]	1.07	1.05; 1.09	3425	0.75	0.00	***	[2.1-150]	1.01	1.01; 1.02	3982	0.28	0.00
University	***	[1.2-15]	1.07	1.03; 1.10	3460	0.56	0.07	***	[2.2-109]	1.02	1.01; 1.02	3991	0.08	0.02
Schools and kinderg.	***	[1.1-9.8]	1.21	1.13; 1.30	3446	0.00	0.54	***	[1.9-37]	1.07	1.04; 1.09	3977	0.00	0.53
Control Variables														
Age	**	cat.	0.89	0.83; 0.96	3463	0.06	0.13	n.s.	cat.	1.02	0.95; 1.10	4009	0.12	0.06
Car Owners	***	[0-1]	0.56	0.45; 0.69	3445	0.02	n.a.	***	[0-1]	0.50	0.36; 0.68	3990	0.14	n.a.
Gender (4)	n.s.	[0.1]	1.15	0.93; 1.43	3471	0.45	n.a.	**	[0.1]	1.21	0.99; 1.49	4005	0.13	n.a.
Income	***	cat.	0.91	0.87; 0.95	3454	0.01	0.40	***	cat.	0.92	0.88; 0.97	3998	0.73	0.03
Season	n.s.	[1-3]	0.90	0.77; 1.05	3471	0.60	n.a.	n.s.	[1-3]	1.08	0.93; 1.24	4007	0.00	n.a.

*** = $p < 0.001$; ** = $p < 0.05$; n.s. = not significant at $p < 0.1$; n.a. = not applicable; cat = categorised.
Shown are odds ratios (OR), 95% confidence intervals (COI), Akaike Information Criterion (AIC) and the results of Brant and Boxtid tests. The lowest AIC values (best model fit) within ±3 are marked in bold font; Range = [max - min]. Build. = building; /GK = per grunnkrets area [km^2]; kinderg. = kindergartens; (1) to (4) indicate the units or coding applied: (1) per 10 segments or axial lines | (2) per 100 segments, axial lines, residents, or employees | (3) per 10^5 m^2 | (4) male = 0, female =1.

Table A2. Results of best subset analyses (proportional odds ordinal regression, not tested for linearity).

High Density GK	Model 1					Model 2			
	n=0	n=1	**n=2**	n = 3	n=4	n=1	**n=2**	n=3	n=4
Reach BRA R9	.	.	**.**	.		PLAv	**1.03*****	1.03***	1.03***
Reach BRA 1000 m	.	PLAv	**PLAv**	PLAv	PLAv	.	**.**	.	.
Prox. Grocery	.	.	**1.05**	1.06*	1.06*	.	**1.07***	1.08**	1.07*
Reach 500 m	.	.	**.**	.	.			0.99	0.98
Reach 2000 m	.	.	**.**	1.01	1.02	.		.	.
Prox. Centre Zone	.	.	**.**	.	.				1.01
Segments/GK	.	.	**.**	.	1.00			.	.
Age	1.00	0.99	**0.99**	0.99	0.99	0.99	**0.99**	0.99	0.99
Car Ownership	0.62***	0.86	**0.88**	0.86	0.87	0.83	**0.86**	0.86	0.87
Gender	1.10	1.13	**1.12**	1.12	1.13	1.15	**1.14**	1.14	1.15
Income	PLAv	PLAv	**PLAv**	PLAv	PLAv	PLAv	**PLAv**	PLAv	PLAv
AIC	3436	3353	**3352**	3351	3351	3353	**3351**	3351	3351

Low Density GK						
	n=0	n=1	n=2	**n=3**	n = 4	n=5
Reach BRA 1000 m	.	PLAV***	1.37***	**1.36*****	PLAv	PLAv
Retail Div. 100 m	.	.	PLAv	**PLAv**	PLAv	PLAv
Building Div. 500m				**1.79***	2.12*	2.04*
Prox. School/Kinderg.	.	.	.	**.**	PLAv	PLAv.
Prox. Uni	.	.	.	**.**	.	0.99
Age	1.10*	1.10*	1.10*	**1.11***	1.11*	1.11**
Car Ownership	0.50***	0.58**	0.57***	**0.57*****	0.58***	0.57***
Gender	1.12	1.14	1.15	**1.15**	1.15	1.16
Income	0.92**	0.93**	0.93**	**0.93****	0.93**	0.93**
AIC	3981	3923	3910	3908	3907	3906

** p> 0.05; **p > 0.01; *** p < 0.001. Bold font indicates the model used in the analyses.

Table A3. High-density GKs, Models 3 and 4.

High-Density GK (n = 1136)

Model 3	OR	COI	P	Wald	**Model 4**	OR	COI	P	Wald
Reach BRA s6 (2)	1.03	1.01; 1.05	**<0.001**	0.48	Reach s9 (1)	PLAv	PLAv	PLAv	0.002
Reach 2000 m (1)	1.02	1.00, 1.04	**0.017**	0.07	3-4x/w | 5x+/w	0.91	0.80; 1.03	0.14	n.a.
Prox. Grocery (1)	1.07	1.01; 1.13	**0.014**	0.14	1-2x/w | 3-4x/w	1.06	0.87; 1.03	0.22	n.a.
Age	0.99	0.91; 1.08	0.87	0.55	1-3x/m | 1-2x/w	1.04	0.97; 1.13	0.27	n.a.
Car Ownership	0.86	0.67; 1.11	0.25	0.15	rarely | 1-3x/m	1.07	1.01; 1.43	**0.008**	n.a.
Gender (3)	1.13	0.91; 1.41	0.26	0.64	Never | rarely	1.09	1.02; 1.16	**0.006**	n.a.
Income	PLAv	PLAv	PLAv	0.01	Reach 2000 m (1)	PLAv	PLAv	PLAv	0.02
					3-4x/w | 5x+/w	1.07	1.02; 1.12	**0.011**	n.a.
					1-2x/w | 3-4x/w	1.07	1.03; 1.11	**0.000**	n.a
					1-3x/m | 1-2x/w	1.04	1.01; 1.08	**0.010**	n.a.
					rarely | 1-3x/m	1.02	0.99; 1.05	0.14	n.a.
					Never | rarely	1.00	0.98; 1.03	0.85	n.a.
					Prox. Grocery (1)	PLAv	PLAv	PLAv	0.24
					Age	1.00	0.91; 1.09	0.95	0.67
					Car Ownership	PLAv	PLAv	PLAv	0.01
					Gender (3)	1.14	0.91; 1.41	0.25	0.63
					Income	0.95	0.90; 1.00	0.043	0.07
AIC: 3350; McFadden Pseudo R^2 = 0.041; Max VIF = 2.24					AIC: 3355; McFadden Pseudo R^2 = 0.044; Max. VIF = 3.43				

Shown are odds ratios (OR), 95% confidence intervals (COI), significance levels (p), Akaike Information Criterion (AIC), McFadden Pseudo-R^2, result of the Wald proportional lines test, and maximum VIF. P-values in bold font indicate significance at $p < 0.05$. Acc. = accessible; Prox. = proximity to the closest; PLAv = violation of parallel lines assumption; n.a. = not applicable; (1) to (3) indicate the units or coding applied: (1) per 100 segments, axial lines, meters, residents, or employees | (2) per 105 m^2 | (3) male = 0, female =1.