One Size Does Not Fit All:

Demographic inequalities in cycling accessibility within the 15-Minute City framework in the Northern Netherlands

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Abstract

The 15-minute city framework is often applied in dense urban settings, but its relevance for low-density regions remains uncertain. This thesis analyses whether cycling-accessible amenities generate equal spatial utility for different demographic groups in Northern Netherlands. Using spatial network analysis, population-weighted postcode centroids and demographic-specific cycling speeds, this study constructs a 0-100 spatial utility index based on amenity availability, destination preferences and diminishing marginal utility from multiple opportunities.

The results display that generalized indicators provide a useful regional overview but mask important demographic differences. The baseline model and population-weighted index are strongly correlated, yet group-specific maps and regressions reveal unequal outcomes. Adults without children achieve the highest spatial utility index scores and appear the least sensitive to low-density environments. In contrast, students, households with children and elderly residents show lower scores in several rural postcodes, mainly because required facilities such as education and healthcare are unevenly distributed. Address density is positively related to spatial utility but explains only part of the variation.

The findings show peripheral 15-Minute City performance cannot be evaluated through a one-size-fits-all indicator. Demographic-specific spatial utility analysis provides a more precise basis for accessibility planning in rural regions.

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1. Introduction

1.1 background

The 15-Minute City framework has gained significant prominence as an urban planning concept. It aims to reduce the automobile dependency, reduce transport emissions and enhance local liveability by offering residents essential amenities within a 15-minute threshold using sustainable transport methods, such as walking, cycling or using public transport (Moreno et al., 2021). Proximity to daily facilities remains a fundamental requirement for the social and economic functioning of local communities. Localizing foundational pillars, such as employment hubs, education and healthcare facilities promotes active community engagement and neighbourhood resilience (Shoina et al., 2024).

This spatial planning emphasis on localized environments is a direct link between the city's physical layout and its fossil fuel reliance. In the study of Huang et al. (2022), they established that low-density environments lock residents in car-dependency and forcing them to drive long distances for basic daily needs. On the other hand, a compact urban infrastructure lowers energy demand, simply because bringing shops, schools and services closer to home replaces long automobile journeys with shorter, possibly active, trips (Monteiro et al., 2023).

Spatial planning literature reveals a prevalent metropolitan bias within the 15-Minute City framework. Most 15-Minute City models are built around dense urban centres, such as Paris and Barcelona, where concentrated facilities easily realize high accessibility scores across all socio-economic groups (Arias-Molinares et al., 2025; Moreno et al., 2021). Downscaling this framework to other geographic contexts requires modification. While the global planning concept theoretically includes walking and public transit, transport planning and research in the Netherlands uniquely places cycling as the primary mode of mobility (Van Kempen, 2010). Within this context, accessibility is operationalized as the potential opportunity to reach essential destinations by bicycle. However, because opportunity to reach essential destinations availability alone does not determine the usefulness of a location for different demographic groups, this study expands traditional accessibility measures by incorporating demographic specific destination preferences.

1.2 Problem statement

The fundamental limitations of the 15-Minute City framework are found in its absolute prerequisites for high density in the urban environment (Moreno et al., 2021). This condition makes the concept conceptually unsuitable for non-metropolitan or rural environments, where active mobility and lower transport energy usage depend on the critical mass of population and address density. In less-urbanized peripheral regions such as Friesland, Groningen and Drenthe, the built environment density finds itself below the urban density of Amsterdam, except for the center of the city centre of Groningen. Due to the lack of residential density, these local facilities are not financially viable and do not experience service growth (McKitterick et al., 2016; van Vulpen et al., 2024). These rural areas are defined by a market-driven centralization of essential public and private facilities (Haan, 2019; NOS Nieuws, 2026). Commercial retail, primary schools and general practitioners are closed or consolidated into larger, municipal hubs to achieve economic efficiency (Caragliu, 2017).

As a result, applying the 15-Minute City framework to a low-density region exposes a structural mismatch between urban theory and peripheral reality. When the distance between residential locations and (centralized) basic amenities expand beyond the 15-minute cycling catchment, the framework does not solely face administrative boundaries: it becomes a conceptual impossibility. For vulnerable residents lacking a private vehicle, this gap cannot be bridged by active mobility alone. Because cycling requires physical vitality, relying on it across longer distances excludes demographic groups with limited physical capability, like elderly and families with young children. Without public transport, this dependency creates transport poverty. Not from bicycle scarcity, but from the functional inability to use active travel for essential services, accelerating spatial exclusion (Zijlstra et al., 2022).

1.3 Research gap

Despite the expanding library of available research on the 15-minute city, a critical research gap persists regarding the model's feasibility within non-metropolitan or rural regions. Because sustainable mobility frameworks acknowledge that low-density areas lack the financials required to support localized amenities, peripheral regions are often ignored in spatial evaluations. This creates a methodological vacuum. Furthermore, where regional accessibility metrics exist, they rely on a simplistic and homogenous commuter profile that assumes uniform travel speeds and equal destination utility (Carvalho et al., 2025). This assumption overlooks how mobility constraints and lifestyle requirements vary across the population (Mouratidis, 2024).

Dividing the population into socio-economic groups is a methodological necessity because cycling speeds and essential amenities and services are fundamentally heterogeneous across the population. Vulnerable demographic groups face a higher exposure to spatial exclusion when services are merged into distant regional hubs (Tönnies et al., 2025). For example, senior citizens often achieve lower average cycling speeds due to natural aging, while relying on localized healthcare infrastructure (Ulloa-Leon et al., 2023a; Vilhelmson et al., 2025). Conversely, younger generations, such as students, show higher cycling speeds but are dependent on centralized higher education and leisure facilities (Ramello et al., 2026). Conventional unweighted models even out these inequalities, masking individual vulnerabilities behind aggregated spatial averages.

Rather than estimating realised accessibility, this framework evaluates the potential spatial utility generated by the current distribution of cycling accessible amenities. By combining network accessibility with demographic-specific destination preferences, it reveals how well centralized infrastructure aligns with the expected needs of different demographic groups.

1.4 Main Question

To what extent does potential spatial utility of cycling-accessible amenities across different demographic groups in the Northern Netherlands?

1.4.1 Sub questions

1. How can demographic-specific service needs and mobility constraints be integrated into a quantitative network accessibility framework?
2. How do the calculated accessibility scores vary between demographic groups across the region, and how does their population weighted combination compare to the baseline model?
3. What is the relationship between local population density and the 15-Minute City compliance for the individual demographic groups and aggregated population?

1.5 Relevance

1.5.1 Societal relevance

Researching the 15-Minute City compliance through a demographic lens is socially urgent for the Northern Netherlands, where the ongoing centralization of private and public infrastructure threatens the regional liveability (Moreno et al., 2021). The proximity to basic services is not an urban luxury good, but necessary for independent living. When local groceries, retail, education and medical practices vanish, people living in the countryside are forced to buy and maintain cars, which creates a major financial burden (Mattioli et al., 2017). There are also vulnerable groups who cannot drive or even lack access to a vehicle (Zijlstra et al., 2022). Think about low-income households, who cannot afford to stay in the city anymore (Booi, 2024), children or elderly. By identifying where demographic demand are mismatched with supply, this study provides regional policymakers a baseline to counter (involuntary) isolation and protect the essential rural services.

1.5.2 Academic relevance

My study directly objects to the continuous urban bias that is dominating sustainable transport literature by testing cycling thresholds where the low-density penalties are the highest. Methodologically, it approached spatial analysis by replacing combined population models with a parameterized distinct demands framework (Carvalho et al., 2025; Mouratidis, 2024). By establishing a baseline and comparing the model against different density levels, my research transforms the academic discourse from basic accessibility mapping towards evaluating how the spatial distribution of amenities generates different levels of utility for different demographic groups.

2 Methodology and materials

2.1 Field of study

Figure 1: Map of the field of the study. The pink buffer zone is utilized as a spatial buffer to locate surrounding amenities.

This research utilizes a spatial network analysis to evaluate the potential spatial utility within the three northern provinces of the Netherlands: Friesland, Groningen and Drenthe, visualized in Figure 1. This area measures 11.389 km^2, 30% of the total area of the Netherlands. The landscape consists of a countryside with small-scale villages and regional cities such as Leeuwarden and Groningen. Because of the landscape, this area serves as an ideal setting to test the boundaries of active mobility frameworks. This allows the evaluation of how declining population density impacts the available services across different demographic groups for all postcodes in the research area.

2.2 Sourced spatial data

To construct the baseline map and analyse the demographic differences in spatial utility, this research combines multiple administrative boundary registrations and open-source spatial datasets. The residential origins are created by using the Basisregistratie Adressen en Gebouwen (BAG), supplied by the Kadaster (2026). This dataset provides addresses and building classifications for every structure in the field of study. Spatial population distributions and regional demographic descriptions are extracted from the most recent file from the Centraal Bureau voor de Statistiek (CBS, 2025), combined to the 4-digit postcode (PC4) level. The transit networks used to compute travel paths is extracted from the Nationaal WegenBestand (NWB, 2026).

The completeness and official validation gave it an edge over the road network of the crowd-sourced OpenStreetMap (Geofabrik, 2026). Although the road network was not comprehensive enough, the data about daily necessities from OpenStreetMap was suitable. Together with institutional education registries taken from Dienst Uitvoering Onderwijs (DUO, 2026) this data was used to map the locations of points of interest (POI's). These layers together form the foundation for the baseline model and the demographic-specific spatial utility models. The processed datasets and model outputs are available from the author upon request.

2.3 Spatial network modelling and origin division

For the calculation the realistic PC4 cycling catchment area, this study uses a network routing instead of Euclidean (circular) buffers. The NWB vector layer was cleaned to exclude roads inaccessible for bicycles (motorways and other motorized vehicle-only infrastructure). The origin nodes of the network were established by aggregating residential addresses (woonfunctie) from the Basisregistratie Adressen en Gebouwen (Kadaster, 2026) into population-weighted centroids for each of the 987 postcodes in the field of study. Subsequently, the networks were generated outward from the centroids using the available street networks.

To execute the demographic demand framework, the regional population is partitioned into four profiles, based on individual age brackets (leeftijdsklassen) provided in the PC4 data (CBS, 2024). To ensure that the subgroups' sum matches the total population of each postcode, without overlapping or double counting, the following aggregation is applied:

- Students: Defined using aged population 15-25, isolating young adults depending on higher education and social spaces. Although this definition inevitably includes non-student working young adults, further subdivision was impossible due to the lack of demographic data at the postcode (PC4) level.
- Adults with children: Defined using a combination of children aged up to 15 years and adults aged 25-45 range. This grouping captures young families.
- Adults without children: Defined using the population aged 45-65. This group acts as a proxy for childless working adults and parents with older children who are less reliant on their parents. This group sees a travel pattern which excludes schools.
- Elderly: Defined using age 65 and older, isolating the senior citizens that see more medical dependencies and a reduced physical travel capability.

Each group was parameterized with group specific cycling velocities and customized destination weights to approximate differences in mobility capability and lifestyle-related service demand. The specifics can be found in Appendix 1.

2.3.1 Population-weighted combination index

To compare the generalized baseline with the demographic-specific outcomes, this research constructs a population-weighted spatial utility index. Instead of treating demographic groups equally for each postcode, the final score for each postcode is a population-weighted average of the four individual group scores. This ensures that the aggregated score reflects the demographic composition of each postcode. Using the individual population counts derived from CBS data, the combined score can be defined mathematically as:

$$A_{\text{combined}} = \frac{(A_{\text{student}} \times P_{\text{student}}) + (A_{\text{family}} \times P_{\text{family}}) + (A_{\text{childless}} \times P_{\text{childless}}) + (A_{\text{elderly}} \times P_{\text{elderly}})}{P_{\text{total}}}$$

A_g describes the 15-minute spatial utility index score for demographic group g and P_g describes its postcode population count. This ensures that when a demographic group is absent within a postcode, its group-specific utility score does not affect the aggregated spatial utility.

2.4 Measures

This section establishes the quantitative framework used to construct the demographic spatial utility index. Rather than treating travel time or proximity as the full measure, the index combines three complementary components: this availability of cycling-accessible amenities, demographic specific destination preferences and diminishing marginal utility from multiple opportunities of the same category. Together, these components estimate the potential spatial utility assigned to the spatial distribution of reachable amenities. The full breakdown of amenity categories is provided in Appendix 2.

The proposed index should therefore not be interpreted as a measure of realised accessibility. Instead, it represents potential spatial utility based on reachable opportunities within a 15-minute cycling threshold. Accessibility forms the transport component of the index, while destination preferences and diminishing returns account for differences in the value of those reachable opportunities. The final output is expressed as a 0-100 index-point scale and should not be interpreted as a percentage of amenity completeness.

To present the potential utility generated by the spatial distribution of infrastructure, the final composite spatial utility index score (A_g) for each postcode is created by integrating three different operational components, visualized below:

$$A_g = \frac{S_{\text{count}} + S_{\text{weighted}} + S_{\text{log}}}{3}$$

- The 'amenity availability' scale (*S_{count})*: This measure calculates a final percentage score (0% to 100%) based on binary checks across the demographic group's required destination categories. For each required category, a postcode receives a 0 if no locations of the required category are present, and a value of 1 if at least one location is present within fifteen minutes from the postcode's weighted population centroid. To convert these separate binary outcomes into a component score, the individual category scores are summed and divided by the total number of required amenities and rescaled to the 0-100 index-point range. If two different amenities have at least one location each present, where five are required, the postcode receives a S_{count} score of 40 index points. This type of binary check is methodologically supported in the framework of Geurs & van Wee (2004).
- Differentiated presence component (*$S_{weighted}$)*: An adjusted metric that applies group-specific utility weights to the binary category values. Not all categories hold equal value and this scale adjusts the importance of the category presence based on the demographic profiles outlined in Appendix 1: Socio-economic profiles in detail (Knap et al., 2023; Mouratidis, 2024). This approach is in line with Litman's (2025) framework, which describes that spatial utility is dependent on demographic demand.
- Logarithmic scale *(S_{log})*: A logarithmic function used to mathematically isolate diminishing marginal utility when multiple amenity locations exist within the reachable network. This implements the utility-based accessibility theory of Geurs & van Wee (2004) and reflects the principle that choice redundancy increases utility, but not linearly.

2.4.1 Grouped destination weighting matrix

To implement the demographic utility framework, the Points of Interest (POI's) are parameterized using an attribute matrix. Instead of assuming every amenity has the same utility for all demographic groups, specific weights were assigned to each category to reflect its necessity for each demographic group (Mouratidis, 2024). This component reflects the relative utility of reachable destinations rather than accessibility alone. As shown in Appendix 1, the weights for each demographic group are derived from the baseline parameter, originally introduced by Knap (2022). The final score for the preference scale is calculated by multiplying the availability score (0 or 1) by its weight:

$$S_{\text{weighted}} = \sum_{c=1}^{N_g} (c_b \times w_c)$$

With the following variables:

- $S_{weighted}$: This is the final calculated differentiated preference score for the demographic group g.
- N_g: The total number of relevant amenity categories, visualized in Appendix 1.
- c_b: the binary availability score within the 15-minute network.
    - $c_b = 1$ if at least one amenity facility is reachable.
    - $c_b = 0$ if no amenities are reachable.
- w_c: the normalized weight for that specific amenity for the evaluated demographic group.

For example, if a category with an assigned weight of 0.10 ($w_c = 0.1$) is present within the cycling catchment ($c_b = 1$), it contributes the full 0.1 to the weighted component. If it is missing ($c_b = 0$), its contribution is 0.

2.4.2 Logarithmic implementation

Besides measuring the presence of amenities, this research also utilizes a logarithmic scale to capture diminishing returns resulting from multiple opportunities within the same amenity category, based on a model made by Geurs & van Wee (2004), where the second or third available location of that category increases utility but with decreasing marginal returns. The logarithmic scale assesses service saturation using the following formula:

$$L_g = \sum_{c=1}^{N_g} \ln(n_c + 1)$$

With the following variables:

- L_g is the total unweighted logarithmic utility value for specific demographic group g.
- N_g describes the total number of amenity categories relevant to the group g, based on Appendix 1.
- n_c is the count of reachable amenities within the specific category.

The addition of the constant 1 within the logarithm is essential. It guarantees that postcodes with no available amenities (n_c) return a value of $ln(1)$, which equals 0 and prevents calculation errors ($ln(0)$ = immeasurable).

To integrate this logarithmic indicator in the final spatial utility index, the raw outputs must be standardized. Because the counts and the logarithmic totals use different mathematical units, they cannot be directly combined. Therefore, a min-max normalization must be applied to the raw logarithmic outputs, converting the data into the 0-100 index-point scale required for the A_g equation:

$$S_{log} = \frac{L_g - L_{\min}}{L_{\max} - L_{\min}} \times 100\%$$

Where L_{min} is the minimum value of the logarithmic utility score, and L_{max} is the maximum score. This process rescales the metric to a 0-100 index, where 0 indicates no utility generated by reachable amenities and 100 represents the highest maximum availability observed within all postcodes.

2.5 Baseline model comparison framework

To evaluate whether the standard one-size-fits-all model is an accurate measurement for the whole population, this research introduces a standardized baseline ($A_{baseline}$) next to the demographic specific models (Mouratidis, 2024). Instead of creating an abstract unweighted control group, the baseline functions as a generalized population profile calculated using the same three measures (S_{count}, $S_{weighted}$ *and* S_{log}) described in ‘

2.4 Measures’. This baseline model differs from demographic models because of its specific parameters, shown in Appendix 1. It uses a travel speed of 17.9 km/h and encompasses all eight amenities with the ‘original’ weights.

Because the baseline is calculated using the same composite index, it represents a generalized spatial utility score rather than observed travel behaviour. By calculating the spatial utility of the standardized baseline and comparing it to the population weighted index, the framework allows the aggregated model output to be compared against the demographic composition of each postcode.

2.6 Exploratory data analysis and visualisation

To address the final research question of how demographic spatial utility variations vary across different geographical environments, this research visualizes the data through the following graphs:

- Boxplots: These plots contrast the median spatial utility scores, interquartile ranges and localized outliers across the baseline, population-weighted and demographic models.
- Scatter plots: These scatter plots visualize each postcode’s spatial utility index score against its address density (omgevingsadressendichtheid) from the CBS (2024). Fitting a non-linear trendline visualizes how spatial utility scales along the address density.

3 Results

3.1 Geographic distribution of spatial utility

This section presents the spatial utility scores (A_g) across the field of study. The outputs of the baseline model are compared to the population-weighted index and the age-grouped models, after which the demographic-specific maps are described.

3.1.1 Baseline and population weighted spatial utility

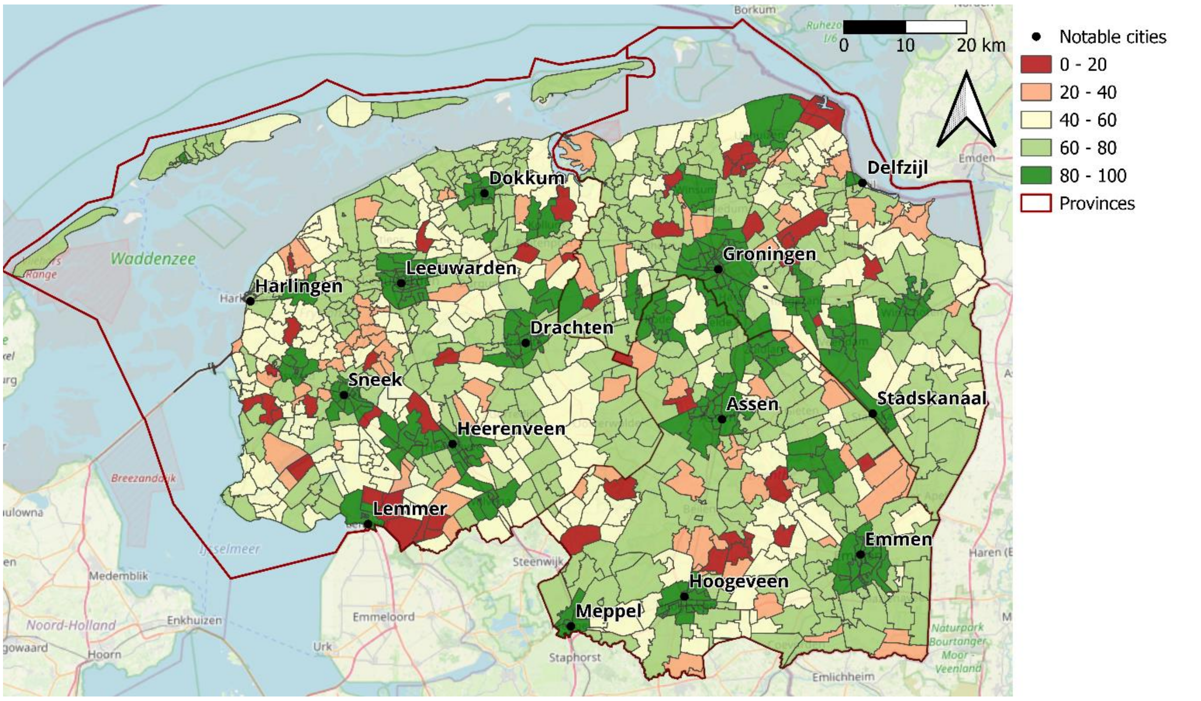

Figure 2 Baseline spatial utility scores.

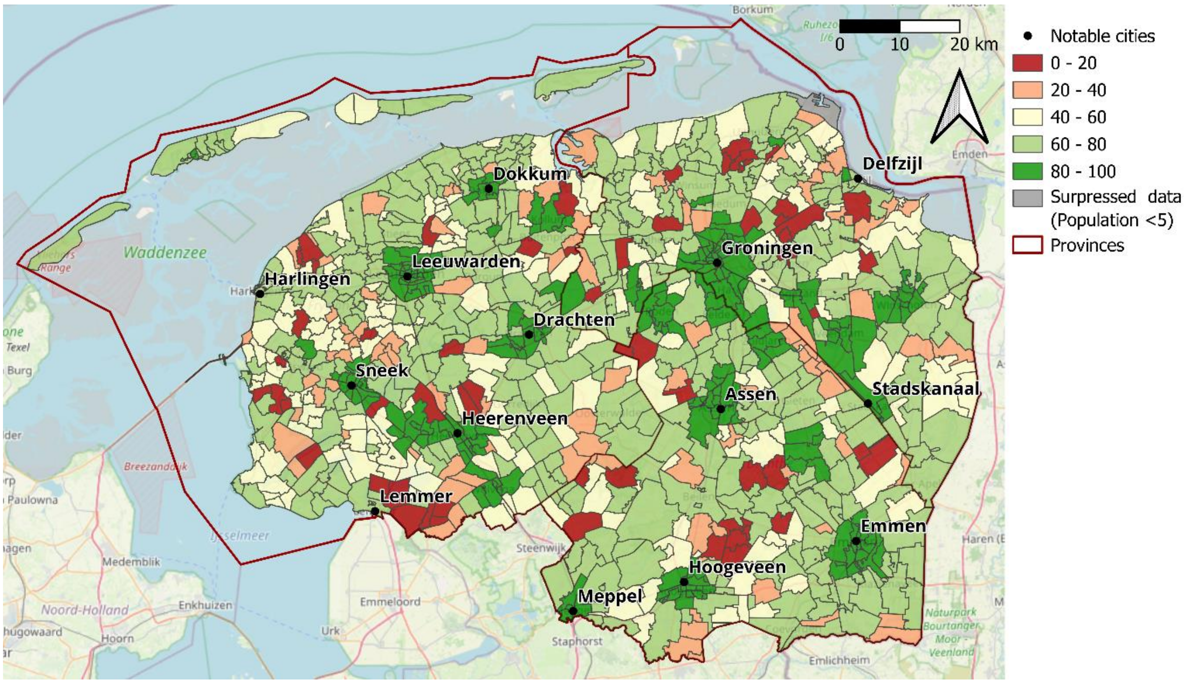

Figure 3 Population-weighted combination scores.

The geographic distribution of the baseline spatial utility model, Figure 2, demonstrates a high degree of spatial aggregation across the field of study. The highest index scores (80-100) are achieved in the largest urban centres, such as Groningen, Leeuwarden, Assen, Emmen and Drachten. The 60-80 class is more widely distributed and appears near the regional centres and larger villages. The 40-60 class shapes an intermediate class across rural parts of Friesland, Groningen and Drenthe. The lowest classes (<40) appear as localized clusters in south-west Friesland and north-east Groningen.

The population-weighted combination (Figure 3) show a spatial pattern that is broadly similar to the baseline map. The 80-100 class remains concentrated around the same urban centres. Some localized differences are visible in the intermediate and lower classes: village clusters around Sneek, Heerenveen and Assen are in higher classes, while some postcodes around Delfzijl and other peripheral locations remain in or more toward lower classes. Overall, the population-weighted map mainly changes local ordering rather than the regional pattern.

3.1.2 Spatial patterns of demographic groups

The spatial distribution is mapped individually across the four demographic groups in Figure 4. Although all demographic groups share largely the same urban centres with high spatial utility, the maps reveal notable contrast in the extent and location of low-scoring (under 60) rural areas.

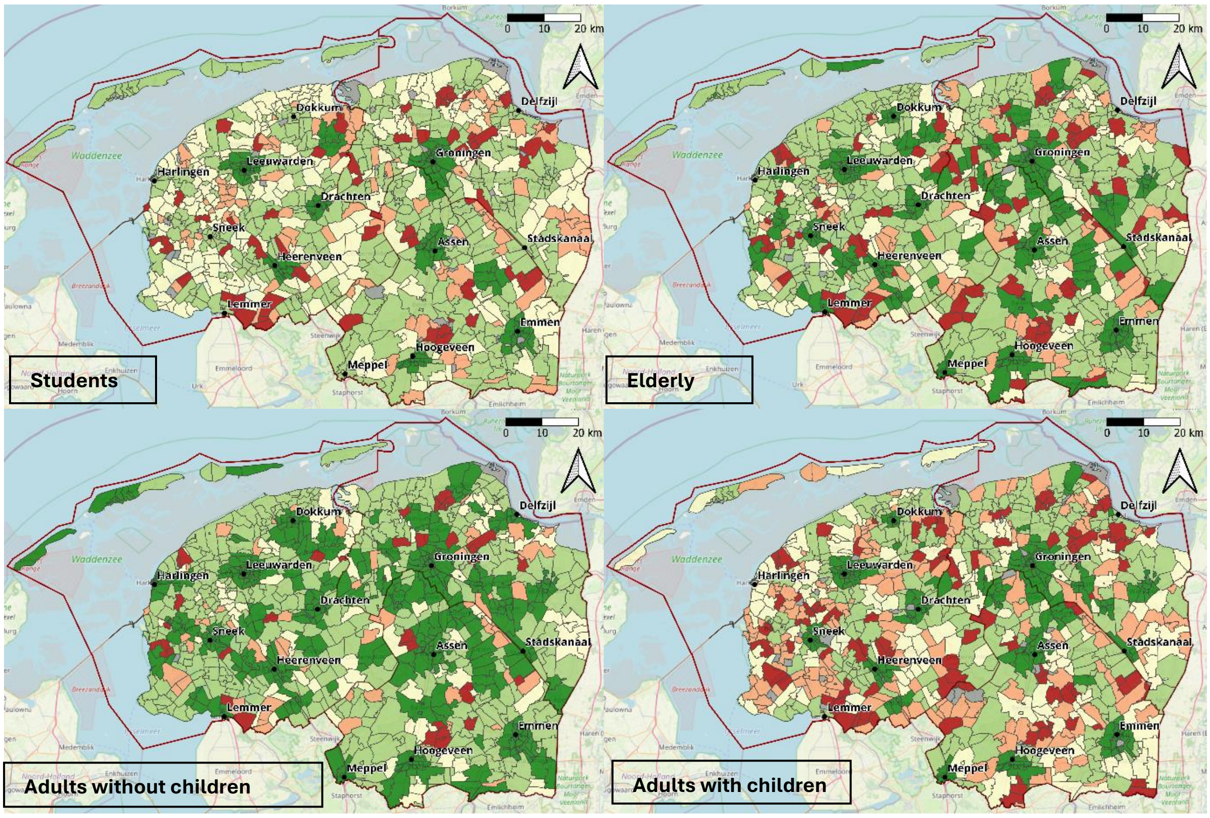

Figure 4: Spatial utility maps of demographic groups. (upper left: Students, upper right: Elderly, lower left: Adults without children, lower right: Adults with children)

Students (Figure 4): This map shows high spatial utility scores (80 – 100) around Groningen, Leeuwarden and Assen. Outside of these urban centres, the map contains a mixture of intermediate and lower-scoring postcodes. Low scores (0-20 and 20-40) are not continuous across the entire rural area but appear in clusters.

Elderly (Figure 4): This map shows high spatial utility scores around larger urban centres including Groningen, Leeuwarden, Assen Emmen and Drachten. The 60-80 class is also present in many surrounding postcodes. Lower classes are visible in rural clusters, especially in parts of eastern Groningen, south-west Friesland and central Drenthe. Compared with the adults-without-children map, the elderly map contains more visible 0-20 and 20-40 postcodes.

Adults without children (Figure 4): This map contains the largest share of higher spatial scores. The 80-100 and 60-80 classes extend beyond the main urban centres into many regional centres and villages. The 0-20 and 20-40 classes are still visible but show less frequent and more spatially isolated compared to the other demographic maps.

Adults with children (Figure 4): This map shows 80-100 and 60-80 scores around the main urban centres and several larger villages. Outside these areas, the spatial pattern is more mixed. The 40-60 and 60-80 classes are more present, while 0-20 and 20-40 postcodes occur in rural clusters. Again, lower classes are particularly visible in western Friesland, north-eastern Groningen and central Drenthe.

3.2 Statistical profile

To evaluate the mathematical relationship and variance across the field of study, this section analyses the correlations, distributions and trendlines between all evaluated models.

3.2.1 correlation between baseline and population-weighted index

Bivariate scatter plots, mapping the correlations across all 987 postcodes were used to examine the relationship between the two indicators for all evaluated models, as shown in Figure 5.

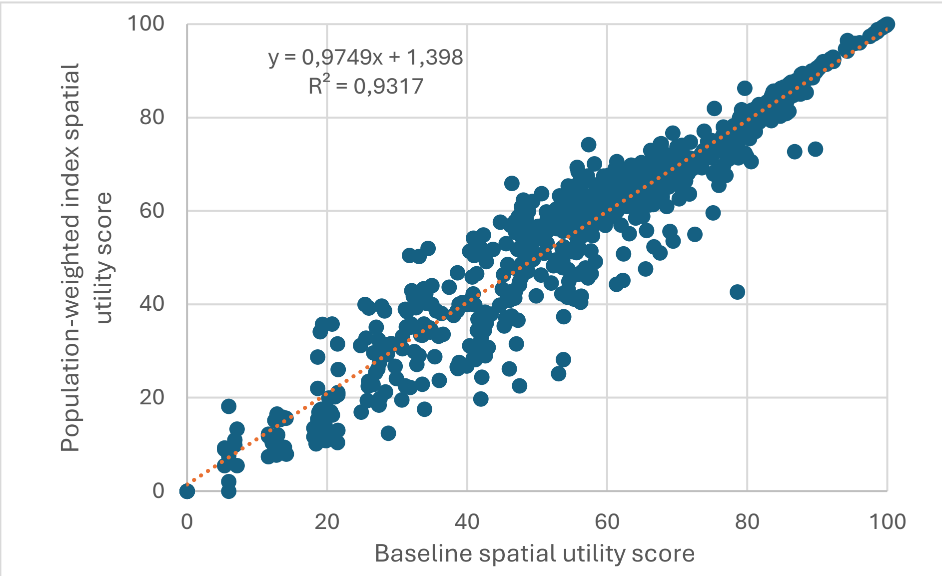

Figure 5 bivariate correlation between baseline accessibility and population weighted index scores.

The calculated 'coefficient of determination' (R^2 = 0,9317) demonstrates that 93.17% of the variance in the population-weighted combination score is accounted for by the baseline model. At the top, the data converges and shows almost total alignment in the urban centres. The highest amount of scattering is visible through the vertical and horizontal deviations, between 20 and 60% baseline spatial utility.

3.2.2 boxplot visualization

To visualize the overall data spread, central tendencies and variances across the demographic profiles, the data is aggregated into boxplots, visualized below in Figure 6.

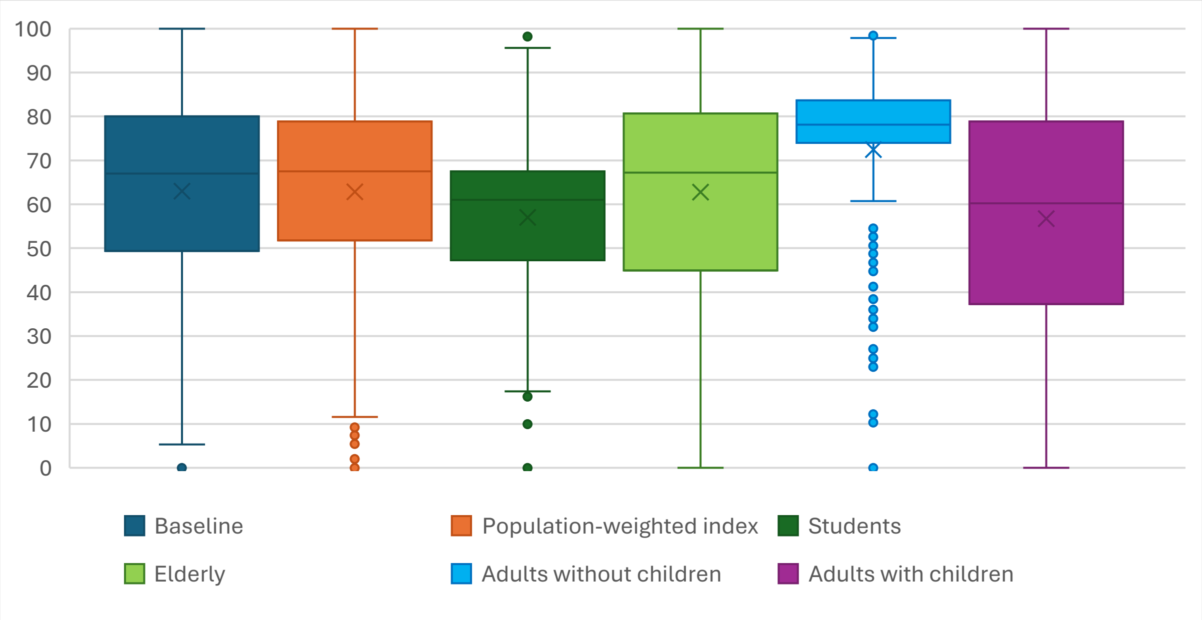

Figure 6 Distribution of spatial utility scores across all models.

Baseline and population-weighted index: Both models show similar central distributions, with their median values also being comparable at 67 index points. However, the population-weighted index has a higher lower-whisker, with more outliers extending into 0-20 class.

Students: Show a median score of about 61 index points, near the lower limit of the 60-80 class. The interquartile range is relatively compressed, while outliers arise at both the maximum (100) and minimum (0) limits.

Elderly: Show a median of approximately 67 index points, placing it within the 60-80 class. The interquartile range spans from 45 to 81, falling in the 40-60, 60-80 and 80-100 class. This shows the broad spread of observations across intermediate and high-score categories.

Adults without children: show the highest and most concentrated distribution. The median is located around 77 index points, placing the central distribution in the 60-80 and 80-100 classes. The interquartile range is narrow, spanning only from 74 to 83 index points. Lower outliers are present, but the central distribution is concentrated in the higher score classes.

Adults with children: Show the highest internal variance of all models. Its median is located around 60 index points, on the boundary between the 40-60 and 60-80 classes. The interquartile range is tall, spanning from 38 to 78 points, meaning that the middle half of the observations is in the 20-40, 40-60 or 60-80 class. Both whiskers extend across the whole range of the score distribution.

3.3 Urbanization gradients and trendline analysis

To analyse how the spatial utility values scale with the address density, this section evaluates the relationship between the model's spatial utility score and address density.

3.3.1 Baseline and population-weighted index comparison

When looking at the baseline model and the population-weighted index, both metrics show a logarithmic trajectory. For the baseline model, the fitted logarithmic trendline has the following equation: $y = 8.8142 \ln(x) + 20.367$. It's calculated R^2-value is 0.3742, indicating that 37.42% of the total variance is determined entirely by variations in address density.

The population-weighted index has a similar logarithmic pattern, with the following regression equation: $y = 8.9716 \ln(x) + 19.448$. The address density gradient shows a nearly identical R^2-value, accounting for 38.06% of the total variance.

Both scatter plots (Figure 7) demonstrate a pattern along the gradient: With an address density below 100 addresses/km^2, spatial utility scores experience high volatility, while an address density of over 1000 addresses/km^2 the spatial utility scores are almost perfect, between 80 and 100% and limited vertical spread.

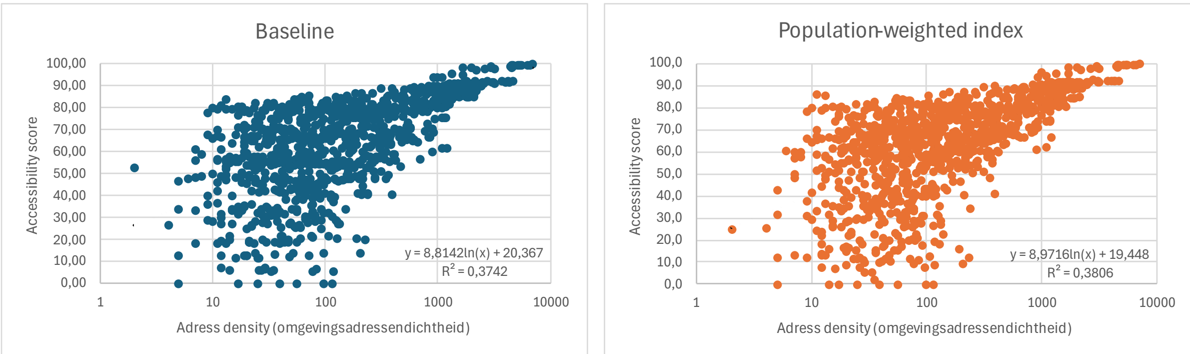

Figure 7 scatter plots of the baseline model (left) and the population-weighted index (right) against a logarithmic scale address density.

3.3.2 demographic groups comparison

Demographic data reveals inequalities across rural and urban areas, with different groups showing different patterns, visible in Figure 8 below.

Students: top left in Figure 8, features a positive distribution with the following trendline: $y = 8.946 \ln(x) + 13.135$. The coefficient of determination (R^2 = 0.3766) indicates that 37.66% of the total variance in student spatial utility is explained by the address density. At lower density (under 100 addresses/km^2), observations are spread across all but the highest (80-100) class.

Elderly: top right in Figure 8, has the following trendline: $y = 9.8949 \ln(x) + 14.712$, with an R^2-value of 0.3712 (37.12%). The data also shows disparities under roughly 100 addresses/km^2 before the datapoints follow the trendline more closely.

Adults without children: This demographic group shows the highest resilience to low-density areas, visible in the bottom-left chart in Figure 8. The trendline follows the equation $y = 7.0825 \ln(x) + 38.104$. This group has a noteworthy high intercept value of 38.104, with few postcodes seeing a spatial utility score below 40 index points even in rural areas. With the highest intercept, this group also sees the lowest R^2-value of 0.2694, where the address density has the lowest explanatory value of the variance.

Adults with children: This group sees the steepest trajectory with the lowest intercept value, with the formula $y = 10.578\ln(x) + 4.9168$. With a R^2-value of 0.3660, the address density explains 36.6% of the total variance. At the lowest address densities (under 100 addresses/km^2) spatial utility frequently drop to 0, but with high variance. Even with slightly higher address density, between 100 and 500, the spatial utility fluctuates between 25 and 85 index points.

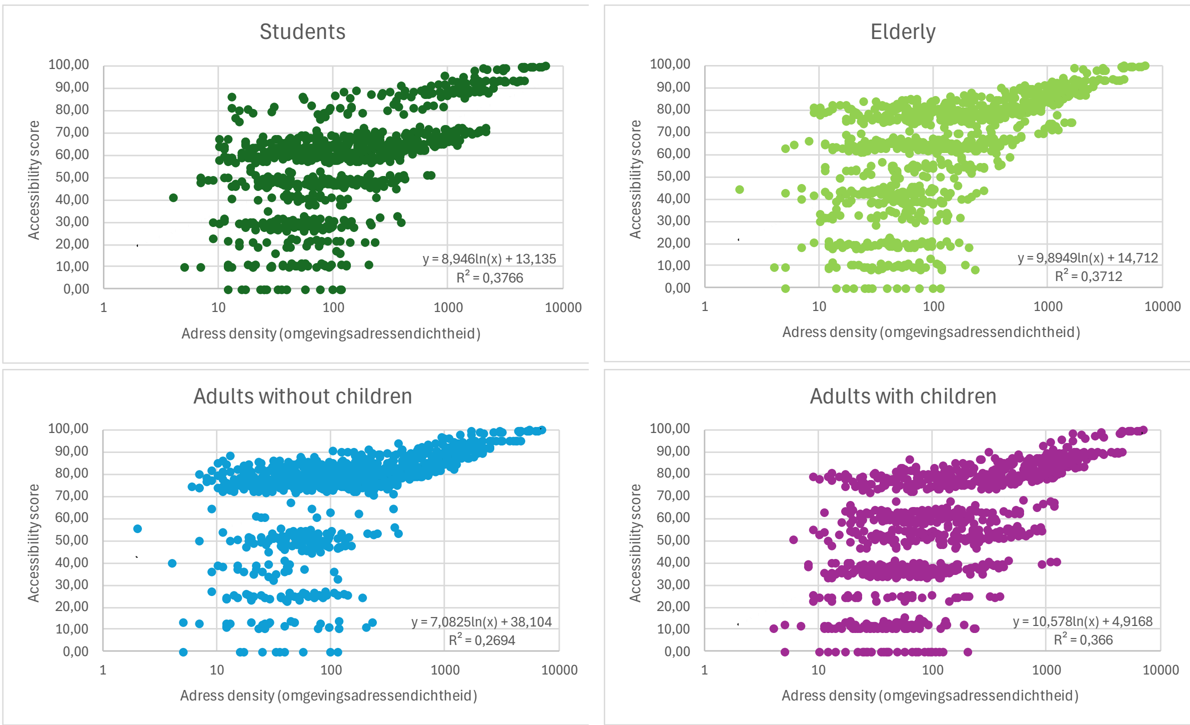

Figure 8 scatter plots of the individual demographic groups' spatial utility scores against the address density on a logarithmic scale.

Overall, the results show that the 80-100 class is repeatedly concentrated around the higher density postcodes, while the 0-20, 20-40 and 40-60 classes differ more between demographic groups and rural postcodes. The maps and scatter plots therefore show a consistent high-score urban pattern, alongside more variable lower and intermediate classes outside of the main centres.

4 Discussion

The results of the postcode-level regression models provided moderate statistical support for the relationship between localized urbanization gradients and demographic spatial utility. While address density is logarithmically associated with higher spatial utility across all demographic groups, the scatter plots in Figure 8 display a distinctly layered distribution, characterized by prominent horizontal bands where postcodes line up along specific index-score thresholds. The discussion reflects on the findings and explores the operational thresholds across demographic groups and considers broader limitations related to model specification, missing variables and data representativeness.

4.1 Interpretation of age-groups disparities and spatial realities

The regression models utilized a log-transformed address density to evaluate the absolute spatial utility outcomes across two indicators (baseline and population-weighted index) and four demographic groups. The baseline ($y = 8.8142\ln(x) + 20.367$, $R^2 = 0.3742$) and population-weighted index ($y = 8.9716\ln(x) + 19.448$, $R^2 = 0.3806$) demonstrates nearly identical trendlines through the data-entries. This high consistency suggests that at a regional planning scale, adjusting for the aggregate population weights does not structurally change the impact of localized density on spatial utility. However, my findings prove that this statistical consolidation is misleading. In practice, the combined metrics function as structural averages that partially conceal group-specific differences in spatial utility within identical administrative boundaries. This phenomenon validates Mouratidis' (2024) critique of aggregated urban planning indicators.

If the physical layout of infrastructure were engineered to accommodate all studied demographic groups equitably, the variance within each postcode would approach near-zero. Instead, my results show that using aggregated indices create a middle-ground score by allowing the high spatial utility scores of adults without children can offset lower scores experienced by more vulnerable groups. This proves that separating the indicators to demographic groups is necessary to reveal how spatial utility is distributed across the region.

The group of adults without children shows the highest resilience to low-density rural environments. Shown in Figure 6, the results return the highest overall median spatial utility score (77 index points), a compressed interquartile range (74-83 index points) and in Figure 8, the highest intercept value (38.104) but the lowest density-driven explanatory power ($R^2 = 0.2694$). The intercept value means that for a postcode with a density of 1 address/km^2, the expected spatial utility score is 38.104 index points. This is a consequence of the parameterized optimization.

By limiting the demand framework to include just four categories (food, retail, bars & restaurants and parks & recreation, Appendix 1: Socio-economic profiles in detail), the adults without children see no impact from the consolidation of schools and healthcare facilities. When combined with the fastest cycling speeds (18.7 km/h), this demographic group appears less sensitive to peripheral service decline. The low R^2-value indicates that address density only explains 26.94% of the variance, leaving 73.06% unexplained. This suggests that for this group, spatial utility is more dictated by other variables besides address density.

On the other hand, adults with children experience volatile and fragmented unequal spatial utility. The regression model in Figure 8 has a steep coefficient (10.578) and the lowest intercept value (4.9168), showing the highest variance with an interquartile range of approximately 40 index points, visible in Figure 6. Because this group's demand framework includes healthcare and primary education, and because the cycling speed is set at only 18 km/h (Appendix 1: Socio-economic profiles in detail), the location of schools and healthcare strongly affect the spatial utility index score. Regional consolidation of schools and healthcare facilities may therefore lower spatial utility in peripheral postcodes where these services fall outside of the cycling threshold (Hagen, 2019; RTV Noord, 2012).

The students exhibit sensitivity to urban centres, where education facilities are located, like Groningen, Leeuwarden or Assen. In the students' scatter plot in Figure 8 is a wide vertical spread (0-70 index points) visible for the address density below 100 addresses/km^2. Even though their cycling velocity is high (18.5 km/h, Appendix 1: Socio-economic profiles in detail), the demand matrix requires a tertiary education and sport facilities, which are not as common as food or retail locations. In the end, the cycling speeds cannot compensate for the lack of localized destination categories and show that students rely on dense agglomerations, validating the residential priorities found by Ramello et al. (2026).

Finally, the elderly demographic group shows vulnerability within my research. Although their median spatial utility (67 index points, Figure 6) and their interquartile range (45 to 81 index points) closely matches the generalized baseline, the urbanization coefficient in Figure 8 (9.8949) show a rural decline that leaves large parts of rural Groningen and Drenthe with low spatial utility scores. This polarization is driven by the cycling speed of only 16.4 km/h (Appendix 1: Socio-economic profiles in detail and their required amenities.

As facilities unify into hub to optimize economic efficiency (NOS Nieuws, 2026), my results capture that seniors in rural areas are left functionally stranded, visible in the boxplot in Figure 6. This systematic shortfall is visualized by the long lower whisker stretching from 45 index points down to 0 without any outliers visible. This proves that service deprivation is a regional reality instead of merely visible in isolated geographic anomalies. These findings validate that uniform guidelines accelerate transport poverty for the older population (Stjernborg & Lopez Svensson, 2024; Ulloa-Leon et al., 2023a).

4.2 Model limitations and missing variables

The modest explanatory power across all models, with density-driven coefficients capping at R^2 = 0.3806, suggests that address density alone cannot explain localized variations in demographic spatial utility. By evaluating supply-side proximity as a metric, the analysis omits residential self-selection, where rural populations frequently relocate specifically to seek environmental quietness and tranquillity (Bijker et al., 2012; Elshof et al., 2017; Pot et al., 2023).For these groups, forcing a 15-minute spatial utility benchmarks misinterprets their personal spatial values as an infrastructure burden rather than an intentional choice (Heinen et al., 2011).

A further limitation is that the proposed index measures potential spatial utility rather than realised accessibility or observed travel behaviour. The model assumes access to a functioning bicycle, so it may overestimate realised accessibility for residents without reliable cycling equipment. The model also assumes that reachable destinations within the cycling threshold are available and relevant according to the assigned demographic weights. In practice, actual use may depend on personal preferences, opening hours, affordability, weather conditions, perceived safety and individual mobility constraints (Geurs & van Wee, 2004). Therefore, the maps should be interpreted as representation of the opportunity structure of the build environment rather than as direct evidence of actual travel behaviour.

Additionally, the asymmetric inclusion of higher education for students versus the exclusion of employment points to a deeper conceptual debate within chrono-urbanism. A growing library of transport literature argues that compulsory motives, such as employment and tertiary education, should stay out of the localized 15-minute city (Caprotti et al., 2024; Ikeda, 2025). Excluding distant employment destinations ensures that the framework remains focused on local neighbourhood spatial utility rather than broader macro-economic spatial structures.

Finally, the network parameters in this research utilize static cycling velocities that fail to capture urban congestion and rural cruising speeds or the rise of e-bikes (Westerhuis et al., 2026). The 15-minute cutoff introduces a “cliff effect” that completely ignores amenities located right outside of the boundary at 16, 17 or 18 minutes. This methodological boundary penalty overstates isolation by failing to address the continuous, marginal travel tolerances, which is a limitation identified in proximity modelling (Geurs & van Wee, 2004; Tomasiello et al., 2023).

4.3 Data quality and representativeness

The spatial utility framework introduced in this study involves some representation problems. While the statistical models account for address-density weighted averages, the spatial utility maps highlight geographic coverage instead of demographic distribution. This results in large rural postcodes to show a more visual prominence, though containing relatively few residents, affecting how regional spatial utility patterns are assessed.

Deriving the relative weights of different amenity categories (Appendix 1: Socio-economic profiles in detail) directly from the baseline data introduces a layer of subjectivity. Because no standardized formula exists for combining different facilities, the final index outcomes are sensitive to the initial weighting choices (Knap, 2022). To minimize this bias, future research could utilize a category presence indicator that measures the proportion of required amenities within 15 minutes. Furthermore, relying on crowdsourced OpenStreetMap data could also be a reason for a difference in urban and rural data completeness. Because voluntary mapping activity drops in rural areas, some real-world rural pathways or local facilities may be missing from the dataset, potentially lowering rural spatial utility index scores (Hecht et al., 2013).

Utilizing individual age brackets introduced in 2.3 Spatial network modelling and origin division as representative demographic groups introduces classification ambiguity. Regional data scarcity required mathematically deriving group-specific amenity weights from baseline weights rather than travel surveys. This created an asymmetric specification where education destinations for students are mapped, but workplace destinations are omitted, oversimplifying non-student spatial utility scores due to limited data availability. Finally, the student category includes all residents aged 15-25, including non-studying or working young adults with different service needs. This introduces an unquantified classification uncertainty, especially in rural postcodes (Bokdam et al., 2010).

A minor limitation is the temporal mismatch between the CBS demographic data from 2024 and the spatial infrastructure and amenity data from 2026, which may create local deviations where recent housing or service changes took place.

4.4 Planning and policy implications

The findings indicate that spatial utility planning in peripheral regions should surpass generalized indicators and instead account for demographic differences in mobility needs. Although the baseline model and the population-weighted index show a strong correlation, the isolated analyses (Figure 8) revealed inequalities that remain hidden with aggregated results. Adults without children continuously attained higher spatial utility scores than households wíth children, students and elderly. As a result, planning decisions based solely on average spatial utility conditions risk neglecting vulnerable populations that depend more on localized services. Future spatial utility assessments should always incorporate demographic differentiation, to determine which population groups are most exposed to service deprivation.

The results indicate that improving spatial utility in rural areas is not only a transport challenge, but also a spatial planning issue. For households with children and elderly residents, spatial utility scores were highly influenced by locations of educational and healthcare facilities. Consolidation of these services may improve economic efficiency but increase the risk of transport poverty and spatial exclusion. Policymakers should assess the demographic consequences of closures against the financial benefits. Instead of pursuing universal compliance with a fixed 15-minute threshold, regional planning strategies may benefit from utilizing a flexible spatial utility target that reflects the reality of the low-density areas. This approach could shift the focus from whether regions meet the 15-minute city framework to whether different demographic groups can maintain access to essential services.

5 Conclusion

This study examined the extent to which spatial utility of cycling-accessible essential services varies across demographic groups in the Northern Netherlands. By integrating demographic-specific cycling speeds and destination preferences into a network analysis framework, this research extends conventional generalized spatial utility assessments, that assume even travel behaviour and service needs.

The results show that spatial utility index score vary between demographic groups. Adults without children achieved the highest spatial utility score and showed the best resilience to low-density environments. In contrast, students, households with children and elderly residents encounter lower spatial utility index scores in many rural areas. The differences were driven by variations in destination specifications rather than cycling mobility alone. While the cycling speeds influenced the size of the accessible network, it could not compensate for the absence of needed facilities like education or healthcare services.

Comparing the baseline model and the population-weighted spatial utility index revealed a strong correlation, showing that the generalized spatial utility indicators offer an acceptable regional overview. However, the demographic analyses showed that these combined measures hide important inequalities. Areas that seem well-served in the baseline model may still accommodate demographic groups facing impactful spatial utility challenges. This finding supports recent critique of the one-size-fits-all model and shows the importance of assessing spatial utility through a demographic perspective.

The address density was positively related with spatial utility across all models, confirming that urbanisation generally increases the availability of cycling-accessible services. However, the limited explanatory power of the regression models indicate that address density alone cannot explain spatial utility results. Spatial service distribution, localized demographic composition and transit networks contribute to shaping spatial utility patterns.

Ultimately, the findings suggest that the main limitation of applying the 15-Minute City framework to peripheral regions is not simply that rural areas achieve lower spatial utility scores, but that spatial utility is distributed unevenly across demographic groups. This study concludes that cycling spatial utility in the Northern Netherlands varies substantially among demographic groups, and that demographic-specific analyses provide a more accurate understanding of spatial utility inequalities than generalized regional indicators. Evaluating the regional performance exclusively through consolidated indicators risks ignoring vulnerable populations facing latent transport poverty. Future accessibility planning must therefore transition from a strict optimization of places toward a more equitable prioritization of heterogeneous people that inhabit them.

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Appendices

Appendix 1: Socio-economic profiles in detail

Table 1: Parameters for 15-Minute City spatial utility mapping for different socio-economic profiles.

	Speed in km/h	KM travelled in 15 min	Cycling speed sources	Categories (amount)	Categories sources
Student	18.5	4.625	(Westerhuis et al., 2026)	Food, commercial, Bars & restaurants, education, sports (5)	(Ramello et al., 2026)
Adults with children (cargo bike)	18	4.5	(Jelmer et al., n.d.)	Education, food, parks & recreation healthcare (4)	(Sánchez-De-Val et al., 2025)
Adults without children	18.7	4.675	(CROW, 2014)	Food, bars & restaurants, commercial, parks (4)	(Elldér et al., 2022)
Elderly	16.4	4.1	(Westerhuis et al., 2026)	food, commercial, recreation & parks, entertainment, healthcare (6)	(Ulloa-Leon et al., 2023b; Vilhelmson et al., 2025)
Baseline	17.9	4.475	(Yan et al., 2026)	All (8)	-

Amenity Category	**Original Weight (Baseline) (%)**	**Students (%)**	**Adults with children (%)**	**Adults without children (%)**	**Elderly (%)**
Commercial	29.90	34.08	49.30		46.09
Food	22.71	25.88	37.44	43.99	35.00
Education	20.17	22.99		39.07	
Sports	8.74	9.97			
Healthcare	6.91			13.39	10.65
Bars & Restaurants	6.21	7.07	10.23		
Entertainment	3.53				5.43
Parks & Recreation	1.83		3.02	3.55	2.83
TOTAL	**100%**	**100%**	**100%**	**100%**	**100%**

Table 2: The weights of the groups were derived from the weights of the baseline. For example, the elderly do not have needs for education (20.17%), sports (8.74%) and “Bars & Restaurants” (6.21%). 100% – 20,17% – 8,74% – 6,21% = 64,88%. The remaining categories are each divided by 64,88%. The commercial category for elderly is calculated by dividing the original 29.90% by 64,88% and gives us the commercial value for elderly, 46,09%. The weights for the baseline are introduced by Knap (2022).

Appendix 2: Categories and their OSM-classes

Category	Description and included OSM classes
Commercial	Non-grocery retail and personal services. Includes clothing shops, department stores, banks, ATMs, hair salons, laundromats, and post offices.
Food	Daily grocery and sustenance retail. This layer includes supermarkets, convenience stores, bakeries, butchers, greengrocers, and open marketplaces.
Education	Learning and child development facilities. Includes kindergartens/daycare, primary schools, secondary schools, and higher education/universities. For households with kids, only elementary schools are selected, and for students only higher education is selected. The baseline includes all types of education.
Sports	Active physical recreation and fitness spaces. Includes sports centers, gyms, swimming pools, tennis courts, and sports pitches.
Healthcare	Medical services and health infrastructure. Includes general practitioners (doctors), dentists, pharmacies, and clinics. Hospitals and specialized medical facilities are purposely left out, since their daily need is a lot lower (Rojas-Rueda et al., 2024).
Bars & Restaurants	Social dining and evening venues. Includes restaurants, cafes, fast food outlets, pubs, bars, and food courts.
Entertainment	Cultural, social, and indoor leisure facilities. Includes community centers, libraries, museums, cinemas, theatres, and arts centers.
Parks & Recreation	Green spaces and outdoor leisure. Includes point-based recreational facilities, playgrounds, and for parks each 100m of circumference counts as a single unit (Crompton, 2001). Smaller areas (<2000m^2 (Knap et al., 2023)) were evaluated for their available amenities.

Table 3: Classification of how OSM classes are combined into usable categories for the mapping of the destinations.