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Activity-based simulations for neighbourhood planning towards social-spatial equity

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ABSTRACT

Urban planners use static analysis techniques like network and proximity analysis to evaluate a neighbourhood's accessibility. However, these techniques do not adequately capture the distributional effects of accessibility on individuals. This paper introduces an activity-based model that simulates residents' daily activities to assess the distributional effects of the built environment (BE) on their accessibility. The model consists of a pipeline to generate a synthetic population covering 96 neighbourhoods in Gothenburg, Sweden, performs origin and destination assignment, and supports four travel modes and different activity types. The synthetic population and the travel demand model are validated across demographic and travel survey data. Additionally, we introduce Trip Completion Rate (TCR), an indicator of distributional accessibility and apply our model to a proposed redevelopment plan for a neighbourhood in Gothenburg to demonstrate its utility.

The results show that techniques used in transportation research can be effectively applied to neighbourhood planning, providing planners with insights into residents' ability to fulfil their daily needs. An advantage of our model is its ability to generate synthetic residents for a neighbourhood and then simulate how changes in the BE affect the resident's ability to achieve their daily needs, thus switching the focus of the analysis from the neighbourhood BE to including the residents that live in it. This paper extends the application of techniques used in transportation planning to neighbourhood planning, thereby empowering urban planners to create more equitable neighbourhoods.

1. Introduction

Urban planning literature has long recognised the importance of the neighbourhood as a key spatial unit where residents interact with their Built Environment (BE) in daily life (Patricios, 2002). Neighbourhoods are the spaces where residents meet their basic needs and interact with each other (Pozoukidou & Chatziyiannaki, 2021). Neighbourhoods also observe urban challenges such as affordable housing, gentrification, and risk of exclusion and segregation for disadvantaged groups, affecting the social cohesion in urban areas (Forrest & Kearns, 2001). Tackling the social disadvantages concentrated in urban areas requires planning strategies based on an inclusive approach to improve the quality of life and social cohesion for all people (EUROCITIES, 2020).

Over the past 50 years, sophisticated urban models have been developed to represent and understand urban spaces (Cottineau et al., 2024). Urban models are simplified representations of urban spaces that aim to understand and explain the processes behind certain urban features using spatial analysis (Cottineau et al., 2024). Urban analytical models have been fundamental in improving the understanding of urban spaces and influencing the everyday interactions of residents with their BE. However, existing models often fall short of incorporating the dynamic interplay between the demographics of neighbourhood residents and their daily routines. Econometric models (Santana Palacios & El-Geneidy, 2022) or network-based approaches like space syntax (Hillier & Hanson, 1984) can only capture glimpses of the city in a fixed frame of reference (Järv et al., 2018).

Parallel to the developments in spatial analysis techniques, transportation modelling has made significant progress in modelling individual behaviour and choices of transportation system users. Computational models of human mobility have traditionally only been used by transportation researchers, and recently, such models have proven helpful in fields beyond transportation (Hörl & Balac, 2021; Strobel & Pruckner, 2023). Neighbourhood planning, however, has not yet seen widespread use of such models as they are not always

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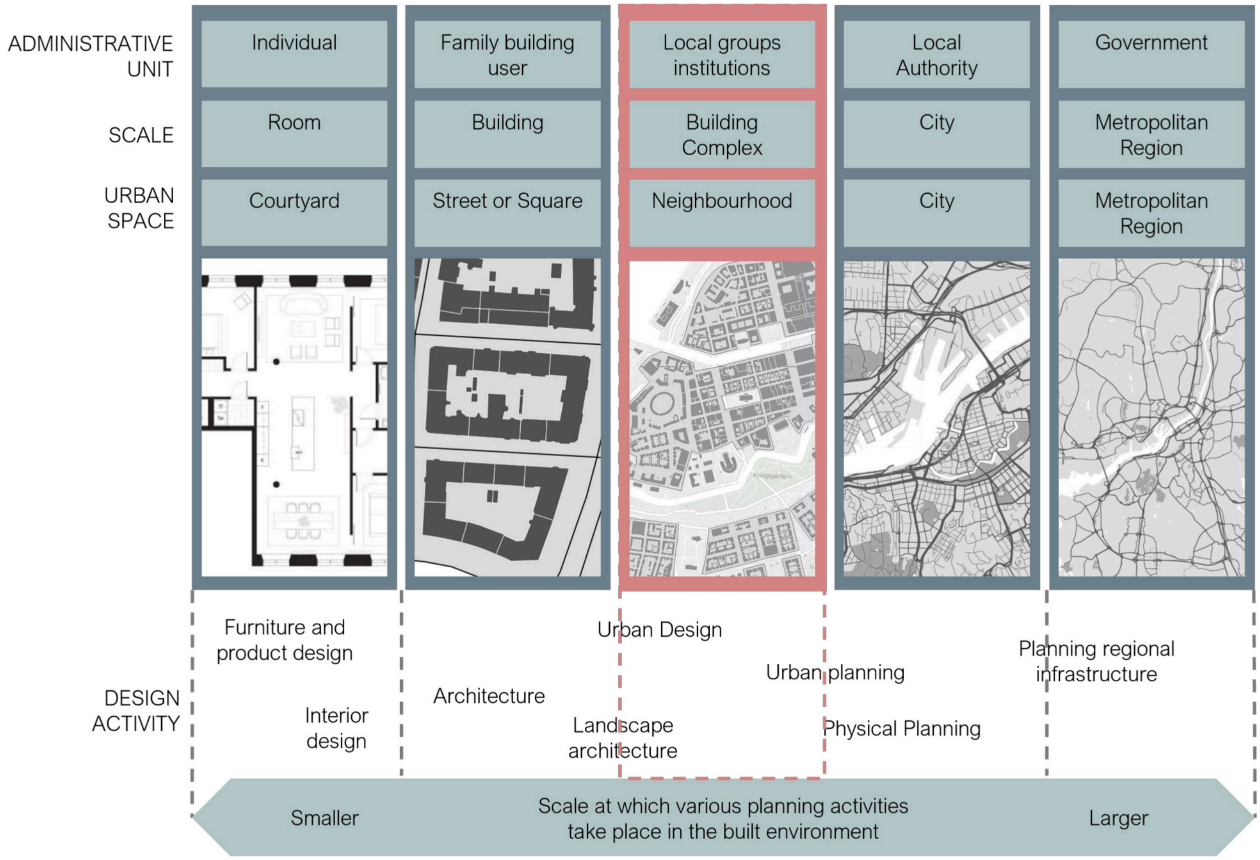

Fig. 1. Scale of design activity in the BE, adapted from (Erickson & Lloyd-Jones, 2001).

replicable, reusable and verifiable (Hörl & Balac, 2021) due to being complicated, difficult to develop, maintain and use, and computationally expensive (Miller, 2023). Recently, Activity Based Models (AcBMs) have increasingly been used in research and for evaluating policy decisions at the city scale, but not in neighbourhood planning. This disconnect results in a critical gap in the neighbourhood planner's toolbox, where the distributional effects of neighbourhood plans on different demographic groups remain unknown (Järv et al., 2018).

Bridging this methodological gap is essential for enhancing the theoretical framework of neighbourhood planning and for practical applications in creating more equitable and responsive urban environments (Järv et al., 2018). As cities grow and diversify, the ability to adapt neighbourhood designs to their residents' changing needs and behaviours becomes increasingly important. This adaptation can lead to urban areas that are more inclusive and accommodating, ultimately improving the quality of life (QoL) for all citizens.

This study aims to explore *how AcBMs can be used by neighbourhood planners to evaluate the distributional effects of planning scenarios on residents* with a focus on dynamic spatial accessibility. To do this, we use the concept of *dynamic accessibility* formulated by (Järv et al. (2018). The authors developed a framework of dynamic accessibility comprising three core components: people, transport and activities. In this framework, "dynamic" is expressed as the variability of the three core components across dimensions like space, time and socio-economic variables. Developing dynamic mobility models tailored for neighbourhood planners allows approaches from the transportation field to be explored in a new light (Strobel & Pruckner, 2023). Dynamic accessibility models can provide neighbourhood planners with the evaluation of the social consequences of their designs, meet the requirements of new residents moving into the neighbourhoods, and elevate the QoL for existing residents (Järv et al., 2018). Planning tools must include the individuals' perspective along with the BE to address the challenge of social equity in neighbourhoods. By shifting the focus of analytical urban models from the BE to the individuals, we aim to illustrate that activity-based approaches can be instrumental to planners in operationalising the social perspective of neighbourhood planning. The novelty of our approach is in proposing and applying an indicator of distributional accessibility to simulated travel patterns of synthetically generated populations on a neighbourhood level. In this study, we demonstrate the value of applying such indicators for practitioners to evaluate neighbourhood planning proposals, focusing on social-spatial equity and providing a nuanced analysis for different social groups.

This paper is organized as follows: First, we provide a background on neighbourhoods and how practitioners have analysed the BE. Then, we present the materials and methods used in this paper. Next, the modelling results and exemplified cases are presented, followed by a discussion of the modelling and the results. Finally, the conclusion section provides an overview of the study and discusses future research directions.

2. Background

The following sections explore the role of neighbourhoods in shaping residents' QoL, the methods used to analyse these urban spaces, and the gaps in these methods.

2.1. Definition and role of neighbourhoods

The concept of *neighbourhood* is both familiar and complex (Choguill, 2008). It is deeply integrated into the urban fabric of cities and the social interactions that take place in them. Neighbourhoods are not only homes to diverse populations but are central to public policy and daily life. Research on neighbourhood planning shows that the BE significantly impacts its residents' QoL (Kyttä et al., 2016), and the neighbourhood is widely used as the scale at which planning policy can be applied (Mouratidis, 2018). In the literature, neighbourhoods are defined based on their scale, size, and composition (Wang et al., 2024). We define the spatial extent of a neighbourhood as a *geographical area that lies between the micro level of a dwelling and the macro level of a city or region* (Mouratidis, 2018) (see Fig. 1). But a neighbourhood is more than its geographical area; neighbourhoods are a collection of neighbours, the people who live within the sub-area (Choguill, 2008).

There is a growing body of literature that investigates the relationship between the BE and residents' QoL. Somanath et al. (2021) explored the relationship between the neighbourhood's BE and residents' QoL using the conceptual framework of urban social sustainability through social equity and social capital. Social themes under social equity arise from interactions between members of society, their physical environment and social infrastructure. Social capital is the emergent qualities of a community as a result of social equity (Somanath et al., 2021). Social equity relates to notions of equitable *availability of* and *access to* services, facilities, and amenities. Research has also shown a strong correlation between improving the sustainability of a neighbourhood and providing equitable spatial accessibility to its residents (Mouratidis, 2021).

The ability of residents to achieve their daily needs within their neighbourhoods contributes to maintaining good health and well-being (Kolodinsky et al., 2013; Luiu et al., 2013; Reis et al., 2000). Studies have shown that people who demonstrate higher levels of autonomy and competence in their daily activities tend to report greater well-being in general (Reis et al., 2000). In addition to individual well-being, notions of equitable access to amenities and services contribute to developing resilient and socially sustainable communities (Widborg, 2017). Compact urban environments, through the density of amenities and homes, allow residents to reach more amenities, thereby increasing the ability to achieve their daily needs.

2.2. From static to dynamic models of accessibility

Accessibility studies have a long tradition of being analytically modelled (Koenig, 1980). The analytical focus of accessibility assessment techniques is usually limited to the ability of the BE to service its residents. Extending this focus to include the resident's ability to fulfil their daily needs allows planners to understand the distributional effects of accessibility in neighbourhoods.

By distributional effects, we refer to the way neighbourhood plans distribute resources, services, and opportunities among residents based on socioeconomic status, age, sex, and family configurations in terms of urban accessibility, such that planning decisions do not disadvantage any single group and instead contribute to fairness and inclusiveness.

Accessibility modelling focuses on the different components of accessibility like walkability, unmet travel needs, latent demand and barrier effects, each with their analytical models (Clifton & Moura, 2017; Eldijk, 2019; Luiu et al., 2018). Van Wee and Geurs (2011) define spatial accessibility as *"the extent to which land-use and transport systems enable individuals to reach activities or destination by means of a combination of transport modes"*. Spatial accessibility has four broad components: land use, transport, temporal, and individual (Geurs & Van Wee, 2004). *Land-use* is the locations and characteristics of where demand is generated and the opportunities to satisfy this demand. The *transport* component is the infrastructure through which individuals can move between the origin and destination to satisfy their needs. The *temporal* component is the times at which demand is generated and the window within which they may be satisfied, and finally, the *individual* component is the demographic characteristics that contribute to the type of demand generated along with the subjective preferences of the individual. Ideally, accessibility measures should consider a combination of all four components; however, in practice, applied accessibility measures focus only on one or a selection of components (Van Wee & Geurs, 2011).

2.3. Activity-based accessibility modelling

In neighbourhood planning, accessibility studies are performed primarily through static analysis of the land-use and transport components: the neighbourhood's street network (Hillier & Hanson, 1984), the morphological arrangements of the built-up regions (Palaiologou et al., 2021), and the location of amenities. The relationship between the ability to achieve daily needs and the BE is also seen in methods developed within transportation planning literature through travel demand forecasting using travel models. In recent years, AcBMs have been favoured over the classic trip-based four-step model. AcBMs realistically capture the entire journey of a commuter both spatially and temporally using a *tour-based* approach (Miller, 2023).

The main advantage of AcBM is the ability to model spatially and temporally disaggregated activity patterns that residents may engage in (Liu et al., 2021), making them an ideal choice for accessibility studies. To capture the distributional effects of accessibility, analytical models must account for both the temporal and individual components of spatial accessibility.

Early research on Activity-based Accessibility (ABA) investigated the transition from trip-based models to activity-based approaches (Dong et al., 2006). Allen and Farber (2020) investigated the social equity impacts of accessibility using AcBM approaches by mapping activity participation deserts where residents have lower activity participation rates due to lower accessibility. The authors reflected that much of current transport equity research focussed on the overall predictive capacity of the travel demand models rather than analysing benefits to vulnerable social groups. Regarding access to activity data, researchers have explored using GPS-based mobility traces as an alternative to travel diaries (Islam, 2010; Järv et al., 2018) to model ABA in urban neighbourhoods, with results stating that such datasets show potential to replace traditional travel diaries. While ABA is an inherent component of applying AcBM approaches, explicit investigations on applying them to neighbourhood planning are lacking in the literature.

An AcBM has different components depending on the purpose of the model and the data available. The main components are a synthetic population, activity sequences, origin and destination assignment, mode choice, and routing.

2.3.1. Population synthesis

A sound synthetic population and synthetic travel demand are essential for transportation models (Hörl & Balac, 2021). A synthetic

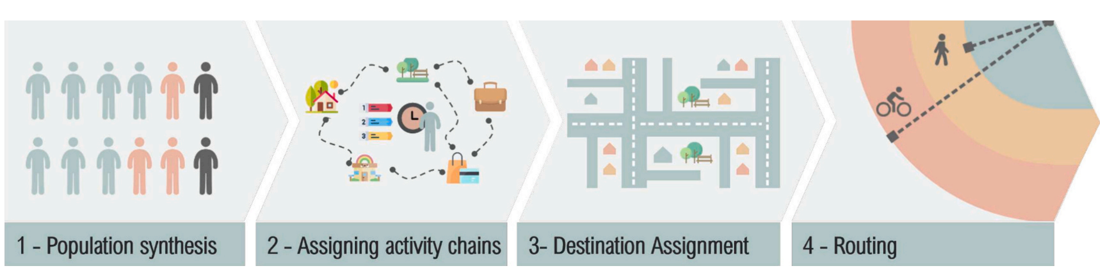

Fig. 2. Steps in the model pipeline (from left to right): Population synthesis, assigning activity chains, origin-destination (OD) assignment, and routing.

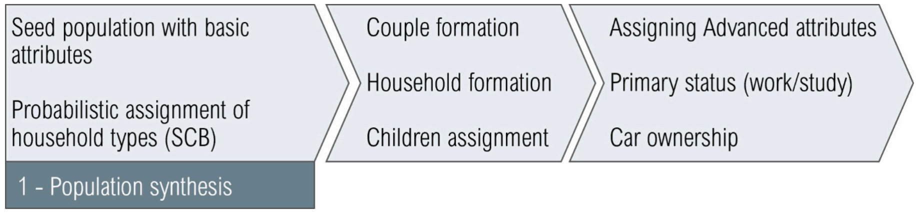

Fig. 3. Population synthesis.

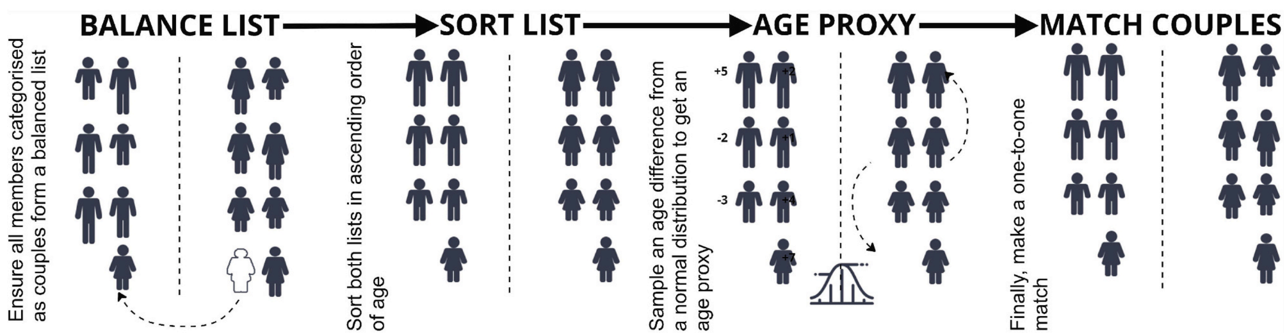

Fig. 4. Age matching mechanism to form couples from individuals.

population is a virtual population of a region where the aggregated demographic distribution follows the real-world population. The most prominent approach to generating synthetic populations is using Iterative Proportional Fitting (IPF), which has been used in several large-scale LUTI models like ALBATROSS, TRANSIMS and UrbanSim (Moeckel et al., 2003). Zhou et al. (2022) created a synthetic population model for Singapore using generative methods like Bayesian Networks (BN) and fitting approaches like Generalised Raking (GR).

Aemmer and MacKenzie (2022) developed a generative model for synthetic population modelling to address the shortcomings of traditional models like IPF and IPU through sub-region modelling and simultaneously modelling individuals and households.

Generative models are promising in synthesising accurate data at a sub-regional level and modelling individuals and households simultaneously. Still, not all regions have access to high-quality micro-sample data like the public use microdata samples (PUMS), as in Gothenburg. In such cases, Monte-Carlo sampling can generate any number of features using more readily available one or two-dimensional attributes from a population register. Using Monte-Carlo sampling, households and persons can sample features in the order they influence each other, resulting in a more realistic population (Moeckel et al., 2003). Barthelemy and Toint (2015) in Belgium developed a synthetic population using similar approaches that scale to country-sized populations. The *VirtualBelgium* project consists of synthetic populations and activity patterns for approximately 10,000,000 individuals and 4,350,000 households across municipalities in Belgium. The model builds on previous work by Barthelemy (2014) that generated a validated synthetic population for Belgium consisting of essential individual characteristics like age, sex, socio-professional status, educational level and driving licence ownership. Further, the model maintains cohesive household units composed of individuals, a feature desirable for simulated household activities in neighbourhoods. To form ontologically connected households with intact relationships between household members, researchers like (Tozluoğlu et al., 2023) have used proxy heuristics based on demographic variables like age and sex.

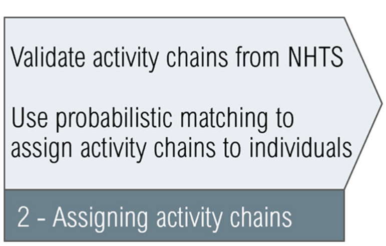

Fig. 5. Assigning activity chains to synthetic residents.

2.3.2. Assigning activity chains

In Barthelemy (2014), the activity chains are sampled from a mobility survey subset matching the individual. Once sampled, the activity chains are stochastically regenerated by further sampling a matching start-time and duration for the activity from the sample. The researchers mention that they first tried to sample the intact survey directly, but this was three times the computational requirement of stochastically regenerating the activity sequence. Using stochastic sampling to fetch activity sequences is more straightforward than using a trip-scheduling mechanism, in which each activity sequence must be optimised for temporal coherence.

In the model by Hörl and Balac (2021), the authors require that a match results in a minimum number of samples from the travel survey. The minimum observations in Hörl and Balac (2021) are set to 20 as

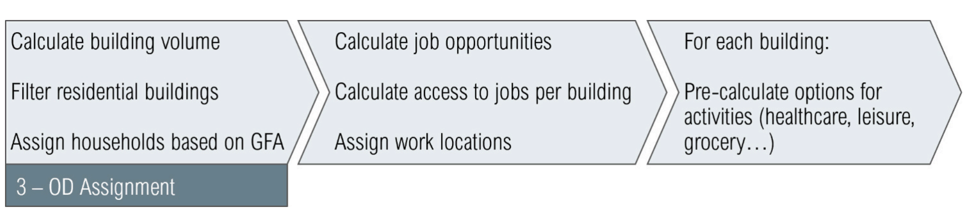

Fig. 6. Origin and destination assignment.

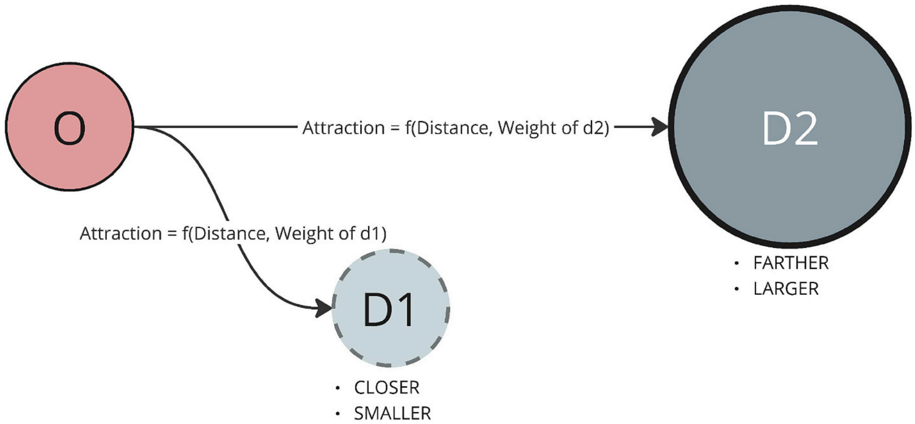

Fig. 7. Illustration of a gravity model for assigning destinations. Based on the gravity model, a resident and location 'O' (red circle) would prefer the larger (or more job-dense) destination 'D2' even though a smaller (or less job-dense) destination 'D1' is closer to the origin. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

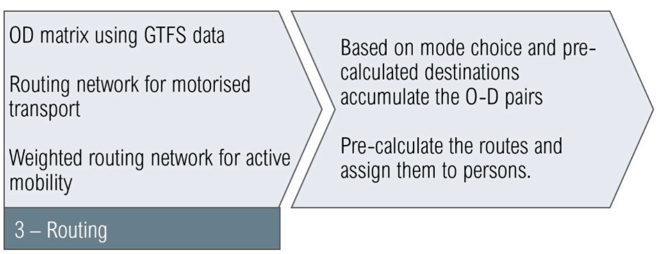

Fig. 8. Multi-modal routing for four modes of transport: walking, cycling, driving and public transport.

compared to the 30 in OMOD by Strobel and Pruckner (2023). Additionally, the authors control car ownership at the household level, which is not done in OMOD. While household units are defined, there are no explicit investigations into validating ontological relationships between household members. Similar hierarchical sampling approaches are employed in other AcBMs (Avery, 2011; Cornelis et al., 2012; Hubert & Toint, 2003).

2.3.3. Origin destination assignment

Researchers in Germany developed an open-source activity-based mobility demand (OMOD) (Strobel & Pruckner, 2023) generation tool based on OpenStreetMap (OSM) (OpenStreetMap contributors, 2017) data to determine what a person would like to do on a given day or week if they had the necessary means of transportation. This entailed generating a population of agents with a detailed activity schedule, and where and how long each activity lasted. The OMOD tool was developed for non-experts to generate a synthetic population anywhere in Germany quickly and was validated on data from 3 cities. The OMOD model limits its scope to activity generation and leaves mode and route choice undetermined for other software like MATSim (Axhausen et al., 2016) or SUMO (Krajzewicz, 2010). For destination assignment, the destinations are picked through a random distance draw based on the activity.

Table 2
Comparison of Survey and Synthetic Proportions for Different Purposes.

Purpose	Survey	Synthetic	Difference
shopping	5.67 %	4.43 %	−1.24 %
education	2.40 %	4.22 %	1.81 %
pickup/dropoff child	5.70 %	4.78 %	−0.92 %
work	21.57 %	23.29 %	1.72 %
leisure	15.33 %	12.91 %	−2.41 %
healthcare	1.47 %	1.46 %	−0.01 %
home	39.73 %	41.26 %	1.53 %
grocery	8.13 %	7.66 %	−0.47 %

Table 1
Summary of data requirements on the neighbourhood and regional level.

Category	Description
Demographics	
Population counts	Population counts for residents in each neighbourhood.
Age group, sex, and household type	The distribution of age groups, sex, and types of households (ex. single, cohabiting partners, married, other) in each neighbourhood.
Housing type	Types of houses, such as small houses or apartment buildings, provide a view of the type of residences in neighbourhoods.
Household size and number of children	Information on the number of members in a household and the presence of younger and older children.
Working population	Data on the working population in each neighbourhood contribute to understanding economic activity and commuting patterns.
Cars	Statistics on total car ownership in each neighbourhood. (Note: The statistics include leased cars but not company cars)
Travel Survey	
National Household Travel Survey	Statistically validated national travel survey including attributes of the respondents such as household type, age group, sex and the detailed travel itinerary and travel data such as mode of transport, travel distance and travel time.
Building Footprints	
Building cadastre	A geospatial dataset of all the building footprints as polygons, including their land use provided by the national building cadastre.
Transportation Network	
Street Network	A geospatial dataset containing the car, bike and pedestrian street network as polylines provided by the transport authority of the region.
Public Transport Schedules	The location and routes of the public transport network, including the departure schedules. The Generic Transit Feed Specification (GTFS) file provided by local transport authorities is used.
Amenities	
OpenStreetMaps Points of Interest	Data on the locations of different amenity types such as grocery stores, barber shops, gyms, etc. This data is collected using crowd-sourced OSM data.

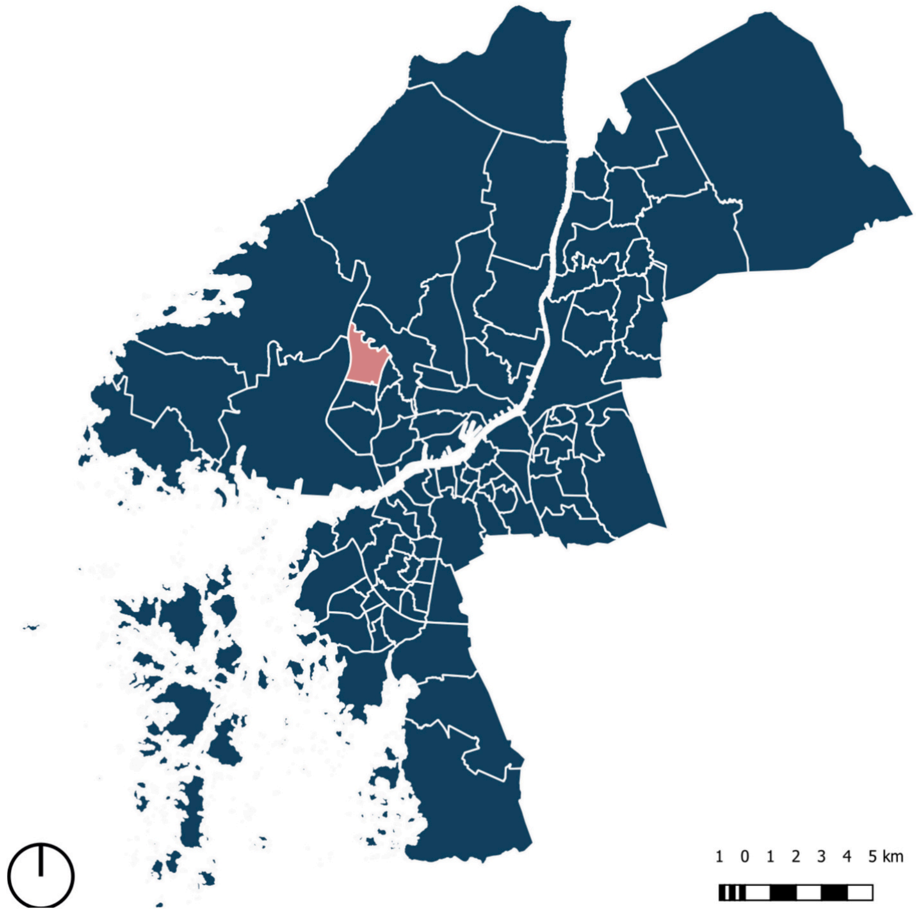

Fig. 9. The primary areas of Gothenburg and the selected neighbourhood of Länsmansgården.

MATSim was used to simulate the traffic assignment. One of the model's drawbacks is that it does not rely on geo-referenced data for different activities or job locations and lacks a mode-choice mechanism.

2.3.4. Mode choice assignment

Two common approaches are adopted in predicting the mode choices of travellers given their demographic characteristics and destination: logit-based models and machine learning models. Logit models belong to a class of econometric models based on random utility maximization (Ben-Akiva & Lerman, 1985). Machine learning models treat mode choice assignment as a classification problem and have recently outperformed logit-based models in several cases (Zhao et al., 2020) and particularly tree-based ensemble models like Gradient-Boosting models have shown promising results in predicting mode choice (Pineda-Jaramillo & Arbeláez-Arenas, 2022).

2.3.5. Routing

Routing refers to determining the path between two nodes on a network. The problem of routing has been referred to by different terminology, such as the shortest path problem (Schrijver, 2012), the vehicle routing problem (Braekers et al., 2016) or the traffic assignment problem (Saw et al., 2015), depending on the application of the problem. In travel demand modelling, the problem is most commonly termed traffic assignment (Braekers et al., 2016). Traffic assignment problems can be classified into two categories based on the complexity simulated (ex., congestion, safety, cost, etc.): static or dynamic (Saw et al., 2015). The simplest form of routing problems is the one-shot static traffic assignment, where a snapshot travel time is measured based on a route generated using a shortest path routing algorithm like the Dijkstra (Dijkstra, 1959), Bellman-Ford (Bellman, 1958) or A-star (Hart et al., 1968) routing algorithm (Bottom et al., 2011). The fundamental premise of the shortest path algorithm is to minimise the cost function associated with a selected route (such as time or distance) defined as weights on the nodes or edges of a network. However, when applied to public transit modes of travel, the availability of the mode and transfer times are also considered, requiring different approaches than traditional shortest path problems (Delling et al., 2015; Fink et al., 2022).

2.3.6. Evaluating synthetic populations

There are no standardised methodologies for evaluating a synthetic population in the literature. This is primarily due to the varying data availability across regions. Most studies evaluate the population's demographic attributes (individually and joint distributions) (Hörl & Balac, 2021; Strobel & Pruckner, 2023; Tozluoğlu et al., 2023). Another metric commonly used to evaluate the similarity of distributions is the Hellinger Distance (HD). HD is a metric that compares the similarity between two probability distributions and is often used in evaluating synthetic data (Bigi et al., 2024; El Emam et al., 2022; Tozluoğlu et al., 2023). The values range from 0 to 1, with 0 indicating that the distributions are identical and one indicating that they are entirely dissimilar. From previous literature that use the HD to evaluate the similarity of synthetic travel distances and duration, we find values between the range 0.13 and 0.28 for a study in Luxembourg by Bigi et al. (2024) and 0.10 and 0.18 for the SySMo model by Tozluoğlu et al. (2023).

2.4. Activity-based models for neighbourhood planning

In previous years, researchers approached different steps of synthesising travel demand, namely the generation of synthetic populations, assigning activities and deriving the travel patterns. However, they are

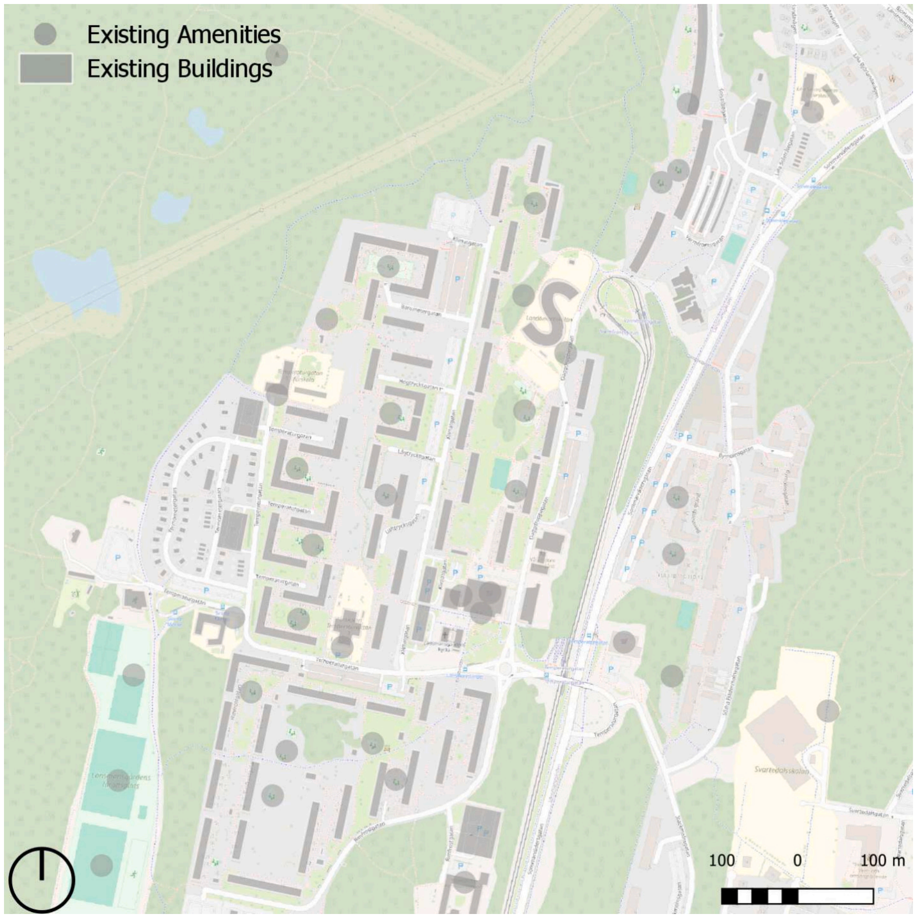

Fig. 10. Existing buildings and amenities in Länsmansgården. Existing buildings are shown as grey building footprints, and existing amenities are shown as circles.

rarely integrated into synthetic travel demand pipelines (Hörl & Balac, 2021). Due to the increased data availability, developments in open-source programming libraries and access to increased computation have resulted in several case studies demonstrating fully open-source and replicable synthetic travel demand pipelines (Zhou et al., 2022). For planners to adopt AcBMs, an integrated pipeline approach can reduce technical barriers, allowing users to focus on the planning process rather than the technical challenges in linking the different model components.

While some researchers have explored the use of AcBMs for neighbourhood planning, these investigations were limited to the aggregated system dynamics of the model in terms of travel metrics. For instance, Liu et al. (2021) developed an AcBM for an area in Beijing, China, to explore the mechanisms of influence of the BE and aggregated population demographics on vehicle miles travelled. Delhoum et al. (2020) modelled a real estate development in Paris, France. The authors used an AcBM and a synthetic population pipeline to simulate a proposal for a new development and present a validation of the representativeness of their model. Though the authors do not evaluate disaggregated trip results, they show that it is possible to synthesise realistic mobility demand from a proposed scenario. These models evaluated the application of AcBMs in neighbourhood planning, but their focus was limited to the service capacity of the BE and not on individual residents. To our knowledge, there have been no explorations of residents of different demographics and their ability to fulfil their daily needs at a neighbourhood level.

3. Materials and methods

This section introduces the different methods and materials used to develop and evaluate the proposed AcBM at the neighbourhood scale. It has five subsections: model pipeline; datasets; trip completion rate (TCR) indicator; model performance and evaluation; and finally, the case study area of Gothenburg, Sweden, through which we exemplify the use of our model. Before we initiated development on the AcBM, we presented a simplified version of an activity-based neighbourhood model with various visualised outputs. 16 architects, urban planners and urban designers working in neighbourhood planning gave feedback regarding the outputs' data inputs, modelling choices, results and visualisations. This consultation phase was part of a larger interview study on urban social sustainability in neighbourhood planning (Reference hidden for blind peer review).

The interview respondents highlighted three important considerations for socially sustainable neighbourhood planning techniques: A) focusing on the individual resident, B) focusing on achieving daily needs, and C) the importance of visualisation to help communicate the results. The recommendations from this consultation phase were then incorporated into the model's design.

3.1. Model pipeline

The proposed AcBM consists of four steps: population synthesis, assigning activity chains, origin-destination assignment (for primary activities like home, education and jobs, and secondary activities like leisure and healthcare) and finally, routing (see Fig. 2). First, a synthetic population is generated per neighbourhood based on neighbourhood-level statistics. Next, activity chains are matched to the synthetic resident to derive their travel demand. A destination is then identified based on the activity type using different mechanisms outlined below. A travel mode is then identified based on their chosen destination, and finally, a

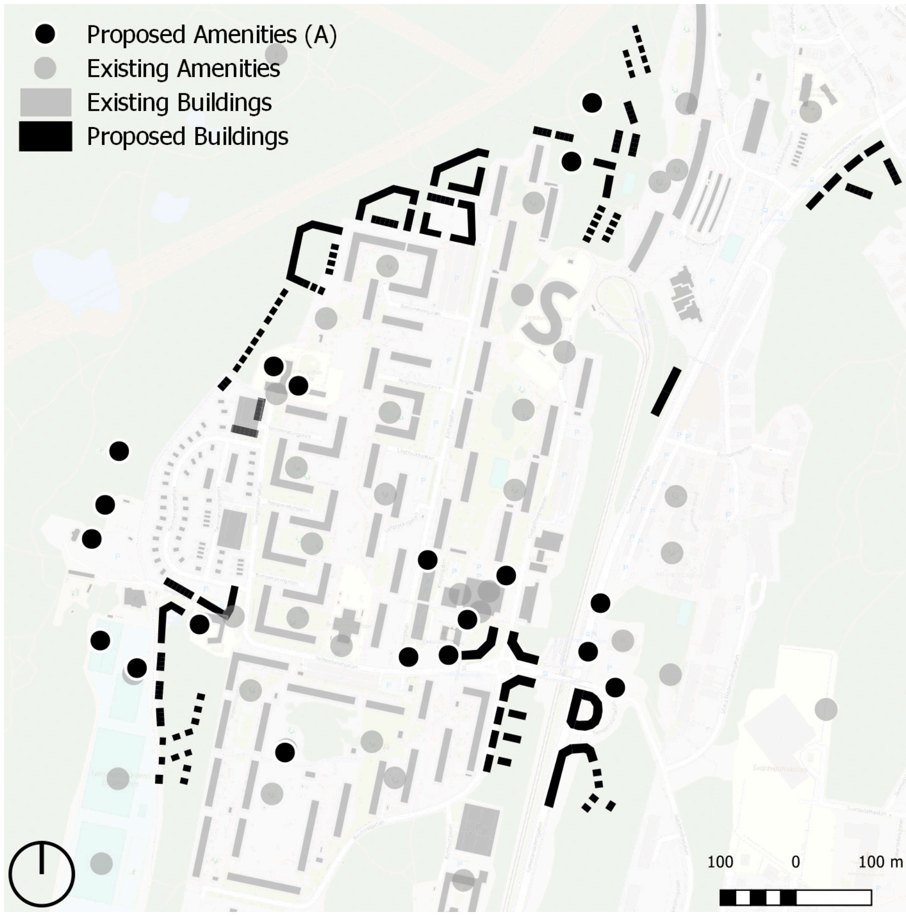

Fig. 11. The proposed residential buildings and amenities (black) with the existing neighbourhood (grey).

route is generated to move them to their destination. For a detailed overview of the model and its documentation, we refer readers to the related data paper that describes the different steps in depth and offers an open-source dataset on the synthetic population of Gothenburg (Reference hidden for blind peer review).

3.1.1. Population synthesis

In this section, we provide a brief overview of the steps to creating the population of the AcBM. Fig. 3 provides an overview of the steps in the population synthesis pipeline.

Most commonly used synthetic population creation methods, like IPF, require a seed population sampled from a real-world population. In the case of Gothenburg, the demographic data is available with joint and marginal distributions across three variables (age, sex, and household type) and can be represented as a three-dimensional matrix. We use Monte-Carlo sampling to incrementally add advanced variables and relationships to form persons and households (Moeckel et al., 2003). To form couples from individuals, we couple the Monte-Carlo sampling with simple age-based heuristics to make the population more realistic. To form couples in the household, we sort two lists of individuals and match them using an age proxy calculated from the age-based heuristic based on (Tozluoğlu et al., 2023) (see Fig. 4).

We continue this process to add additional attributes and finally create entities for persons, households, buildings, and homes. A person belongs to a household that lives in a housing unit within a building (see Fig. A1). For advanced variables like whether the person has a car, works, studies or is inactive, we use machine learning-based attributes trained on a subset of the NHTS that contained residents that reside in the Gothenburg region. Finally, each household is assigned a home through a House entity within a Building entity.

3.1.2. Assigning activity chains

Based on the demographic attributes of the person and the two predicted attributes of primary status (working, studying or neither) and car ownership, we perform a statistical matching of activity sequence from the NHTS based on D'Orazio et al. (2006) and Namazi-Rad et al. (2017). Fig. 5 provides an overview of the steps in assigning activity chains to residents. The activity sequences contain a series of activities (i.e. home, work, leisure, education, picking and dropping children, grocery shopping and other shopping) that a person would be engaged in along with the start time of the activity. Sampling activity sequences directly from the NHTS simplifies the synthesis pipeline by removing the need for a dedicated activity scheduling mechanism in our pipeline.

However, before the activity chains are sampled, they are pre-processed. Only activity chains for persons living in the Gothenburg region are used. Further, we consider the trip weight provided in the NHTS for the representativeness of the activity sequence. Finally, they must be valid activity sequences that satisfy the following conditions: the activity must not have a zero or negative duration unless it is to pick up or drop off children; the activity cannot overlap another activity; the total duration of all activities must start and end at home; and finally, all activities must have a mode assigned to them. The preprocessing resulted in 87.5 % of activity sequences being valid. For further details on the statistical matching in this paper, we refer readers to the data paper that documents the synthetic population modelling steps (Reference hidden for blind peer review).

3.1.3. Mode choice prediction

For the mode choice prediction, we first pre-process the NHTS data only to include residents in Gothenburg and exclude any out-of-municipality trips. Then we train a Gradient Boosting model using the

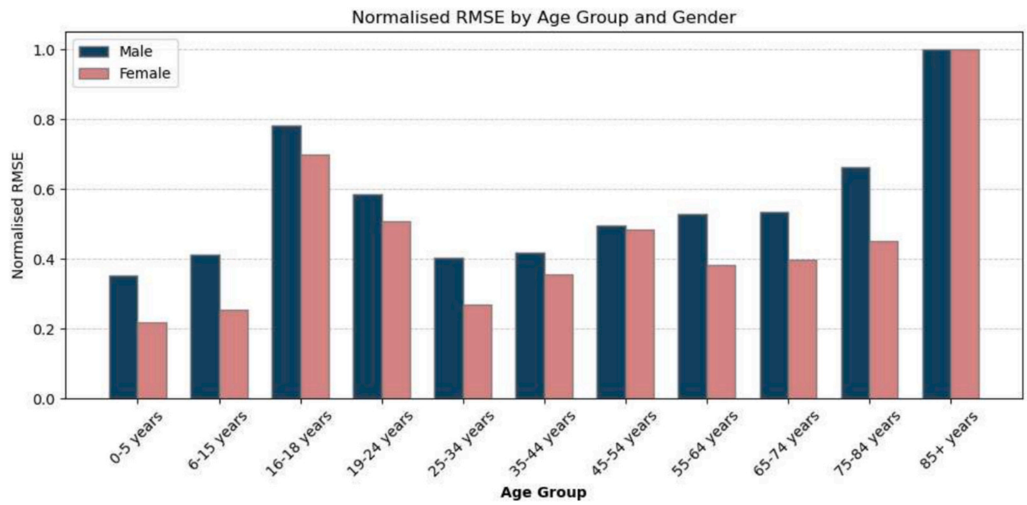

Fig. 12. RMSE in all Gothenburg neighbourhoods for male and female residents across age groups.

Table 3
HD for median distance and duration of different purposes.

Purpose	HD Median Duration	HD Median Distance
shopping	0.124	0.135
education	0.170	0.265
pickup/dropoff child	0.164	0.156
work	0.094	0.112
leisure	0.072	0.123
healthcare	0.185	0.181
home	0.118	0.120
grocery	0.092	0.131

age, sex, number of persons in the household, number of children, number of cars in the household, primary status (working, studying or neither), house type and household type to predict whether the mode choice is a car, public transport, walk or bike based on Pineda-Jaramillo and Arbeláez-Arenas (2022). The model performance was first evaluated on a training set, and further hyperparameter tuning was performed to improve prediction accuracy.

3.1.4. Origin destination assignment

The OD assignment is divided into three steps: home assignment, primary location assignment, and secondary location assignment. Home assignment is done by assigning households to appropriately sized homes based on the average home sizes in the city and the available residential housing in a neighbourhood. Fig. 6 provides an overview of the steps in carrying out the OD assignment.

We use a gravity model for the work location assignment (see Fig. 7). The gravity model uses the distance from the home and the density of jobs in a 1000 m radius (see Eq. 1). The influence of the job density and the travel distance is calibrated for each neighbourhood to the surveyed SDN median work distance using a Nelder-Mead optimisation algorithm. After calibration, the model probabilistically assigns workers to job locations based on the attraction.

$$A_{ij} = \frac{J_j \cdot W_k}{d_{ij}^{\beta} + \epsilon} \tag{1}$$

Eq. (1) Unnormalized gravity model equation for the attraction between home i and job location j.

where:

A_{ij} : Attraction between home i and job location j,

J_j : Job density at location j,

Table 4
HD for median distance and duration of different modes.

Mode	HD Median Duration	HD Median Distance
car	0.106	0.114
walking	0.189	0.154
bicycle/e-bike	0.135	0.168
public transit	0.094	0.093

W_k : Density weight based on SDN k,

d_{ij} : Distance between home i and job location j,

β : Distance decay factor,

ϵ : A small constant added to avoid division by zero, $\epsilon = 10^{-5}$.

For higher education, a subset of the 10 closest locations of higher education facilities from the OSM points of interest (PoI) is first considered, and a random location is selected from this subset. Finally, for the secondary location, we categorise OSM PoI tags (Table A2) into the activity categories available in the NHTS to create a set of options for each activity that is close to the home (see Table A1. Depending on the secondary activity, the model randomly assigns a destination for each person from the considered options.

3.1.5. Routing

We use a single-shot static traffic assignment mechanism for the routing in our model. The routes between the origin and destinations are selected based on the mode of transport assigned to the resident without consideration for turn restrictions, terrain or congestion. Once a mode is assigned, the respective travel model is selected, and the appropriate routes are generated. We store the pedestrian, cycling and driving network as an undirected graph object (Csardi & Nepusz, 2006) for three modes of transport, to form a multi-modal routing model (see Fig. 8). We use the maximum speed for the driving network from OSM to determine travel time along the street edges. For the pedestrian and cycle networks, we select the route with the shortest distance (Dijkstra, 1959). For the public transportation network (Fig. 8), we use the public transport timetable data in the r5py (Fink et al., 2022) python library to create a travel-time matrix for all origin-destination pairs for Gothenburg at a 250-m grid resolution. We use this travel-time matrix to query travel times when the assigned mode is public transport.

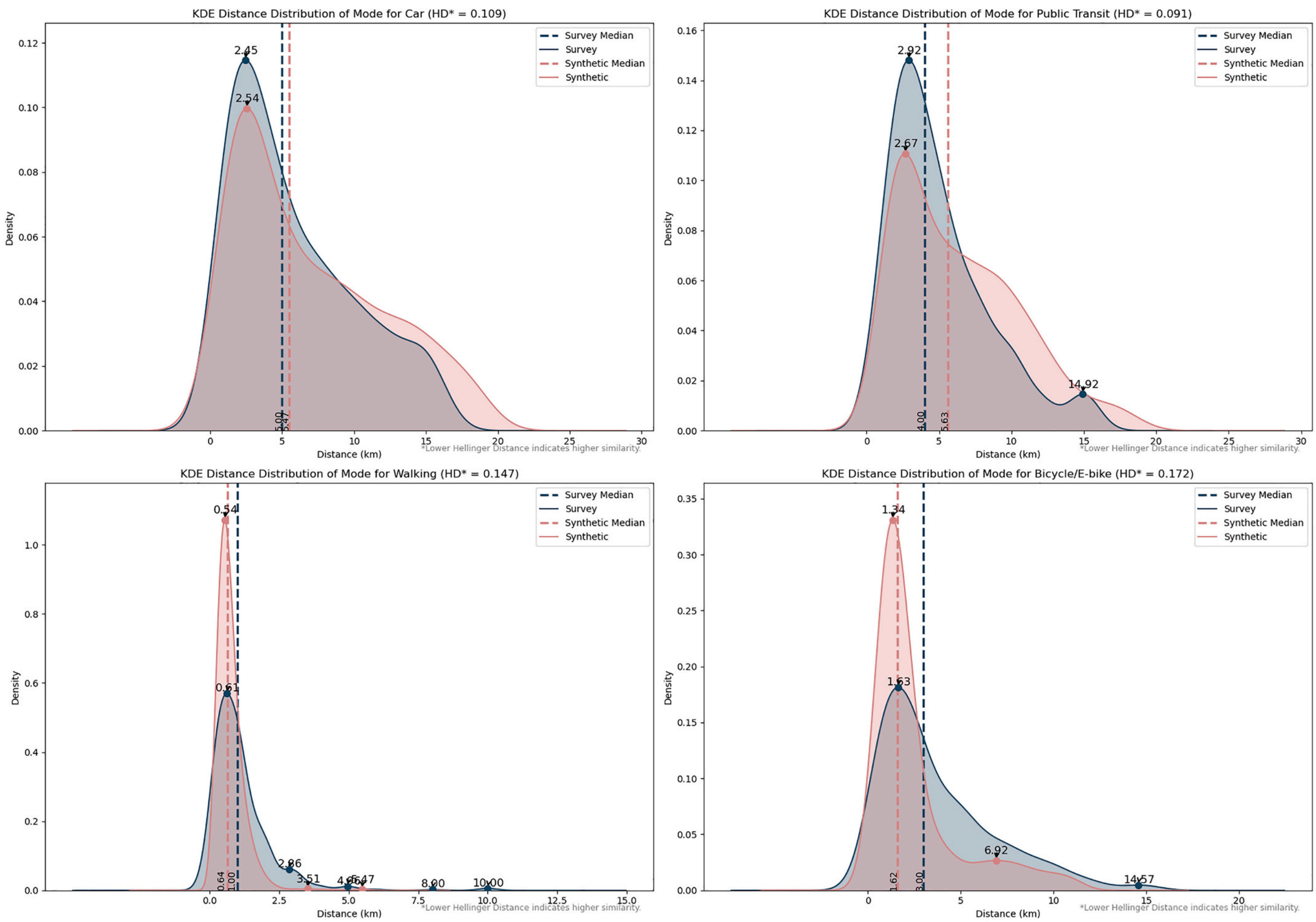

Fig. 13. Density plot comparison of the median travel distance per mode of travel.

3.2. Datasets

Five main datasets are required for our model: demographic statistics, the National Household Travel Survey, building footprints, transportation networks, and the location of the amenities in and around the neighbourhood. The following sections elaborate on each of the datasets mentioned above. Table 1 summarises the data requirements for the model: (See Table 2 for comparisons with synthetic population.)

3.2.1. Demographic statistics

For Gothenburg, Statistic Sweden (SCB) provides a data portal, which includes demographic data at the neighbourhood (i.e. primary area) level (Gotebörgs Stad, 2022). This data is available for all years, from 2003 onwards and connects to the model via an online Application Programming Interface (API), enabling the creation of synthetic populations for different years. The model uses population data from 2019, when the total population of Gothenburg was 579,281. We chose 2019 as the demographic composition of residents after 2019 may have changed due to the COVID-19 pandemic compared to the travel survey data used. The model, however, can connect to data sources from any available year on the data portal.

3.2.2. National household travel survey

A National Household Travel Survey (NHTS) is a survey of the household travel patterns in a region. The Swedish NHTS is conducted annually and comprises around 35,000 respondents (RVU, 2017). The survey includes questions about the household demographics, including the number of cars, children, household size, etc., and the travel patterns of the household members through a travel diary. The travel diary consists of a record of the travel patterns of the household members for 24 h consisting of the following information, among others: start and end time of the trip, the mode of transport used for the trip, and the purpose of the trip.

3.2.3. Building footprints

The Swedish cadastral agency Lantmäteriet (Lantmäteriet, 2022) provides a dataset of the footprints of all the buildings in Sweden. We first calculate the building height using LiDAR data, then assume a typical floor height of 3 m and calculate the number of floors in each building. The number of floors is used to calculate the population per floor and the total feasible population for each building.

3.2.4. Transport network

For the transportation network, we consider walking, cycling, cars and the public transportation infrastructure. To build a multi-modal transportation network, we use the road centre-line data from Trafikverket (2024) and from OpenStreetMap contributors (2017) (OSM), and the General Transit Feed Specification (GTFS) public transport timetable data from Trafiklab (2024).

3.2.5. Amenities and points of interest

For residents to fulfil their daily needs, we require a dataset of

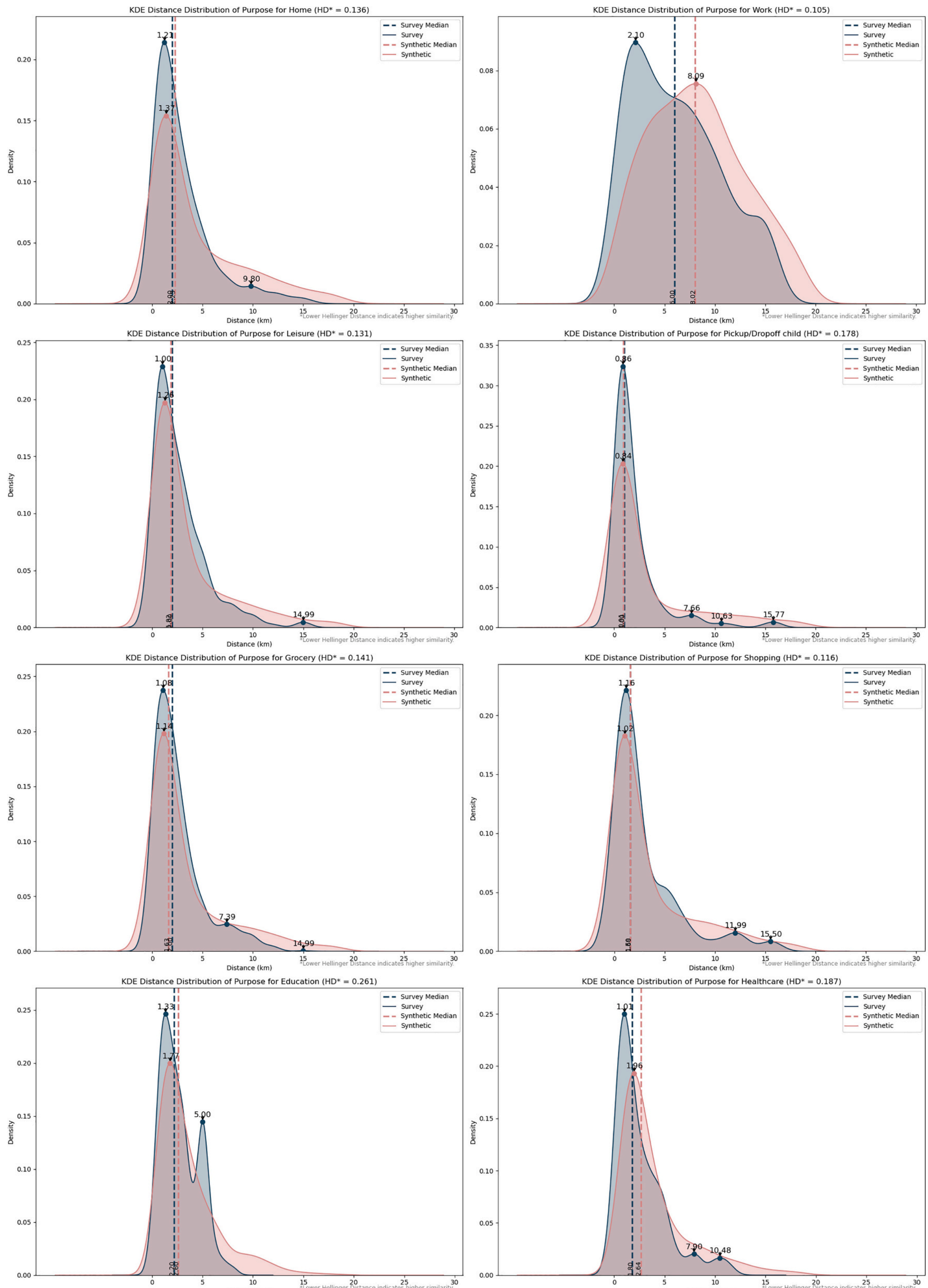

Fig. 14. Density plot comparison of the median travel distance per purpose of travel.

amenities. We gather amenities from OSM and map each amenity and point of interest category to the activity demand categories. Additionally, the city of Gothenburg maintains a database of different daycare centres, preschools, schools and playgrounds administered by the city (Göteborgs Stad, 2023). The synthetic population pipeline fetches the locations of the amenities and stores them in the list of available amenities. The model can also filter the list of amenities for individuals depending on their demographic characteristics. Research on leisure

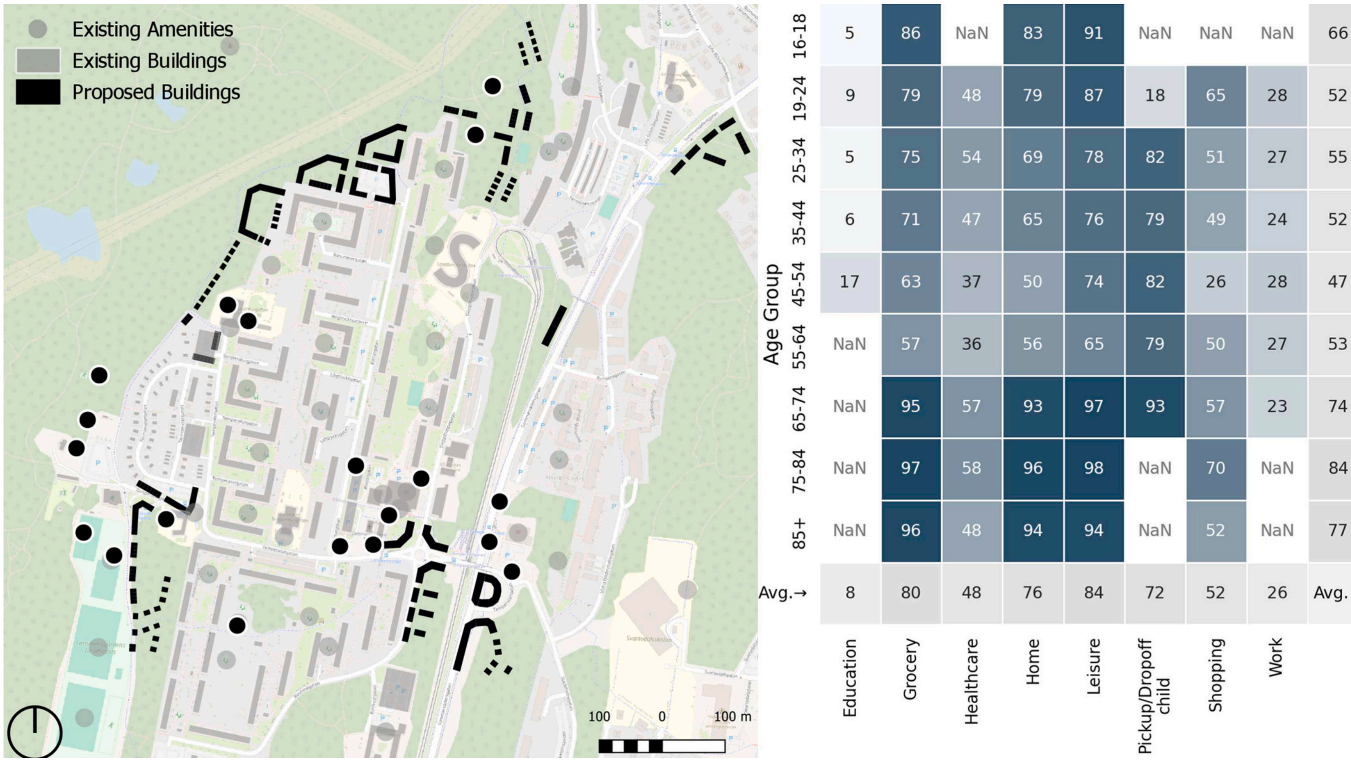

Fig. 15. Baseline scenario with added residential buildings and no additional amenities (left). Neighbourhood TCR for all trips under 15 min with existing amenities (right). TCR is the proportion of all trips that are completed under 15 min.

destination choice of parents with children has shown that leisure activities for children are increasingly supervised and with longer travel distances with a preference for organized leisure activities. Therefore, parents accompany children or align their leisure destinations with their children (Nordbakke, 2019). For example, parents with children under 17 prefer playgrounds and sports amenities for leisure activities.

3.3. Trip completion rate

Since we want to evaluate each resident's ability to fulfil their daily needs, we must create a composite indicator representing this ability across demographic variables. To achieve this, we propose an accessibility indicator called Trip Completion Rate (TCR) (Somanath et al., 2022). TCR is a *person-based* measure of access that represents residents' ability to meet daily needs against evaluation criteria (like distance or time). Using a synthetic population with detailed travel data, we can overcome some operational issues related to assessing individual accessibility highlighted in previous sections.

Eq. 2 shows the expression for TCR. Since the indicators require some form of aggregation and often have different units of measurement, we scale the data between 0 and 1 and present these values as percentages of the subset. The TCR indicator allows planners and decision-makers to incorporate their normative values of equity by defining a threshold value (or condition) such as travel time, trip distance or emissions (for example, all trips under fifteen minutes) and evaluate the distributional effects of neighbourhood planning across the three core components of dynamic accessibility, i.e. people, transport modes and activities, aggregated on the individual or the household level (Järv et al., 2018).

$$TCR = \frac{\text{Number of trips that meet condition}\, k}{\text{Total number of trips in the set}\, A_f} \tag{2}$$

Eq. (2) Equation to calculate Trip Completion Rate (TCR).
Where:

A : Set of all trips.

A_f : Subset of trips from A that meet a specific condition.

$cond(k)$: A conditional operator that serves as the evaluation criterion for trips in A_f.

For example, if the trip attribute is trip duration, then $cond(k)$ might be

$$< 15$$

to evaluate all trips completed in under 15 minutes.

Dividing the completed trips with the total number of trips within a subgroup gives the proportion of the affected population relative to the total population of the subgroup. This proportion can highlight issues across subgroups, regardless of their population size. However, model users must use caution while interpreting the results, especially for values at the extremes, such as 0 and 100, and the results must be further examined for the presence of realistic trips in the first place.

We rely on equal weighting of all variables in the TCR. As for aggregation and visualisation, TCR can be represented as a two-dimensional $m \times n$ matrix M, constituting row vector h and column vector y describing two categorical variables in the data set.

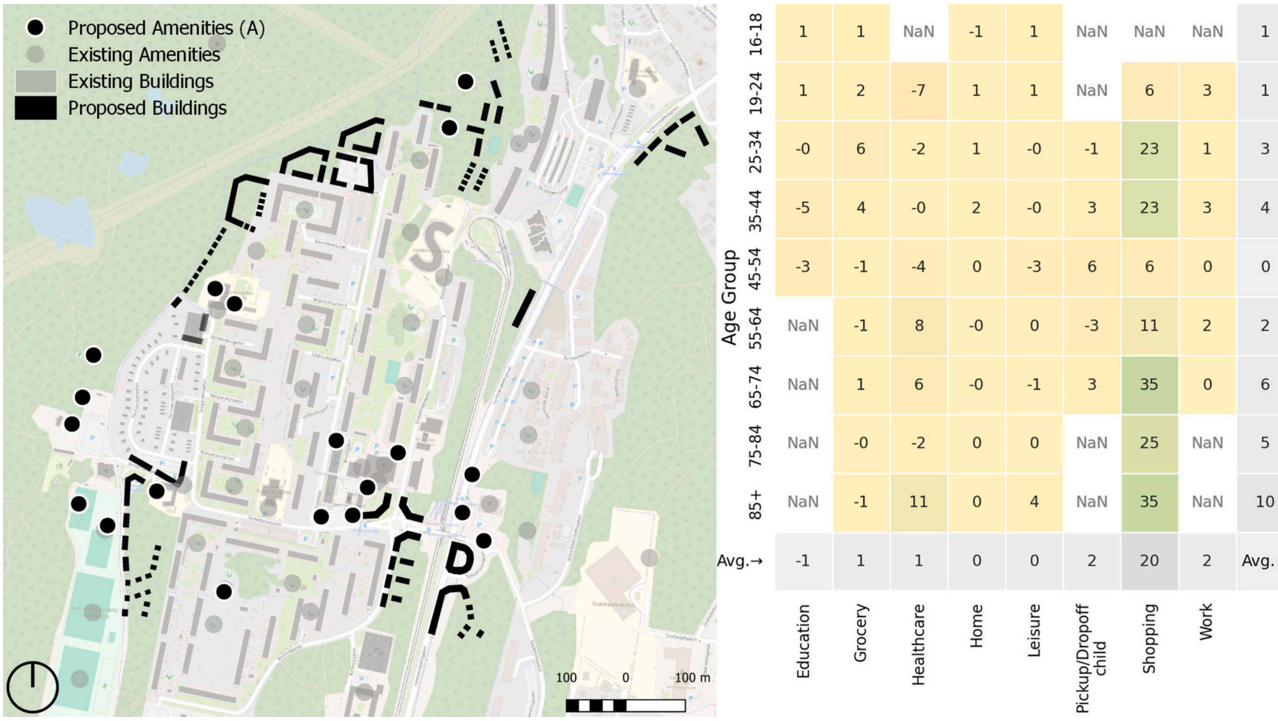

Fig. 16. Scenario A with added residential buildings and proposed playgrounds, preschools and shopping amenities (left). Relative increase/decrease in TCR for all trips under 15 min compared to the baseline scenario (right). TCR is the proportion of all trips that are completed under 15 min.

$$\begin{array}{c|c} & \xrightarrow{\hspace{6em}} h \\ \Big\downarrow y & \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{3}$$

Eq. (3) Matrix representation of TCR.
Where:

M : The TCR Matrix.

h : First categorical variable (such as age group).

y : Second categorical variable (such as trip purpose).

m : The number of categories in row h.

n : The number of categories in column y.

Such that:

Each element of the matrix is x_{ij}, where i and j are the categories of the categorical variables selected. x_{ij} lies at the intersection of the two categories i and j. For instance, if h is the age group consisting of seven categories (16–24, 25–34, 35–44, 45–54, 55–64, 65–74 and above 75), and y is the trip purpose consisting of ten categories (i.e. business travel, education, groceries, health, home, leisure, picking and dropping kids, shopping, work and other), x_{11} represents the TCR for all 16 to 24-year-olds who complete all business trips under the set criteria.

3.4. Model performance and evaluation

For the proposed model, we look at the joint distribution across different variables to validate the synthetic population against population and travel survey data. We calculate the normalised Root Mean Squared Error (RMSE) for all neighbourhoods across the age, sex, primary status (working, studying or neither) and car ownership variables to identify the average number of residents misclassified. For the activity sequence sampling and mode choice, we look at the difference in the proportions of different modes and activity purposes at the city level. For the origin and destination assignment, we look at the difference in median travel time across different modes of transport and activities. Finally, using the HD metric, we present the distribution similarity between the synthetic dataset and the survey data across travel distances for different modes and purposes.

3.5. Study area

The proposed model is developed for the neighbourhoods in Gothenburg. Gothenburg is Sweden's second-largest city after Stockholm, with a population of over 600,000. The city is divided into four hierarchical, administrative divisions: urban areas (*stadsområden* or SDN), intermediate areas (*mellanområden*), primary areas (*primäromraden*) and base areas (*basområden*), from the largest to the smallest. The primary areas of Gothenburg serve the same urban function as a neighbourhood. There are 96 primary areas in Gothenburg (see Fig. 9) ranging between 0.23 km^2 in the central areas and 57 km^2 on the outskirts, with a higher population density in the central neighbourhoods compared to the outskirts.

While the city is known for its commitment to sustainability (Göteborg & Co, 2023), it has been struggling with issues of segregation in the suburbs (Costa, 2022). Gothenburg has seen the highest population increase among all municipalities in 2023, while Sweden's overall population growth declined (City of Gothenburg, 2023). The growing population, coupled with a rate of construction that lags housing demand, has led to tremendous stresses on the city's housing infrastructure (Wilen & Reiter, 2023). The city has plans to make significant investments in six of the city's most vulnerable neighbourhoods over the coming years to make them more equitable and inclusive (Costa, 2022).

To exemplify the utility of the proposed model, we apply the model to a redevelopment plan for the neighbourhood of Länsmansgården (see Fig. 10), one of the vulnerable neighbourhoods identified by the city of

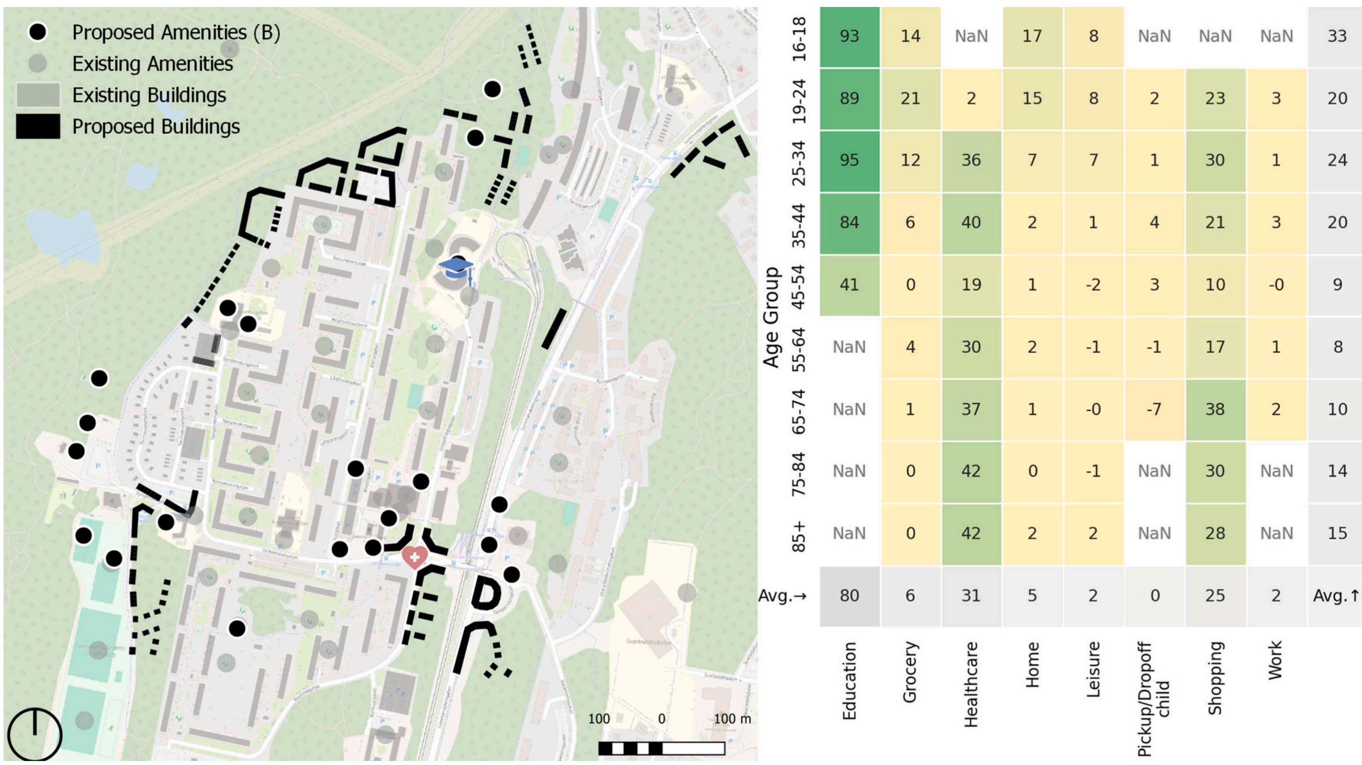

Fig. 17. Scenario B with added residential buildings and proposed preschools, playgrounds, adult education, healthcare and shopping amenities (left). Relative increase/decrease in TCR for all trips under 15 min compared to the baseline scenario (right). TCR is the proportion of all trips that are completed under 15 min.

Gothenburg. Länsmansgården has a population of around 6000 residents, with around half being born outside Sweden. The neighbourhood also has a higher level of unemployment (12.3 %) compared to the municipal average (of 6.6 %). Over 90 % of the building stock in this neighbourhood was built between 1961 and 1970, with over 90 % of housing stock being multifamily houses. Länsmansgården is well-connected by the public transportation system and enjoys good access to nature and primary schools in the neighbourhood, along with two supermarket chains. The closest public healthcare centre is 2.1 km away.

3.6. Planning scenarios

As a part of the initiative to reduce segregation and revitalise the six most vulnerable neighbourhoods of the city (Costa, 2022), the city has proposed new housing amenities and increased linkage to the city's transportation network for the neighbourhood of Länsmansgården. These plans are publicly available[2] and form the basis of our case. The proposed plan for Länsmansgården (see Fig. 11) includes nine new multifamily houses and 152 single-family or row houses, leading to an increased population of about 760 households and approximately 1900 persons. The proposal also includes a new public square with different amenities, new primary schools and extensions to existing schools.

The city aims to incorporate the *15-min-city* concept for the new neighbourhood to reduce car usage. The TCR indicator can facilitate an evaluation of this goal by setting a threshold of 15 min on the travel time variable. Hence, the TCR is evaluated on a travel time of 15 min across age groups and trip destinations.

To demonstrate the application of our model to plan new amenities for the neighbourhood, we first consider a baseline where the new residential buildings and the new population are added to the neighbourhood. Then, we create two planning scenarios for the amenities to be added to the neighbourhood. *Scenario A* includes shopping, preschool and leisure amenities based on an existing proposal for the neighbourhood. *Scenario B* includes additional amenities like healthcare and adult education. Healthcare and adult education were identified in the public consultation with the residents. Finally, *Scenario C* is presented, where we repeat scenario B under a car-free setting. We do this at the mode choice prediction step. For activities where the mode choice assigned is the car, we replace this with to the next most likely mode of travel. This is done to investigate the potential for a car-free neighbourhood. The purpose of separating scenarios A and B is to demonstrate how practitioners could iteratively explore planning scenarios. Each scenario is simulated ten times with the TCR values averaged to smooth stochastic variations induced by the proposed model.

4. Results

In this section, we present the results of the proposed model's performance in terms of how representative the synthetic population is compared to the real-world population and whether the model can capture the nuances of the local BE to affect the travel patterns of the synthetic residents. Finally, we demonstrate the utility of TCR as an indicator of residents' ability to fulfil their daily needs, following the design interventions in the case study neighbourhood.

4.1. Model performance and evaluation

On average, across all Gothenburg neighbourhoods, variables of age and sex show that less than 3 % of the total synthetic population is incorrectly classified. While this number is low, looking at the individual distribution of attributes does not tell us much about the overall quality of the synthetic population. A more reliable metric is the error recorded in the joint distribution of multiple variables using RMSE. An RMSE of between 1 and 3 can indicate that, on average, in any given neighbourhood, there are 1–3 incorrectly assigned residents across the joint

[2] https://goteborg.se/wps/portal/start/goteborg-vaxer/hitta-projekt/stadsomrade-hisingen/biskopsgarden/program-for-biskopsgarden

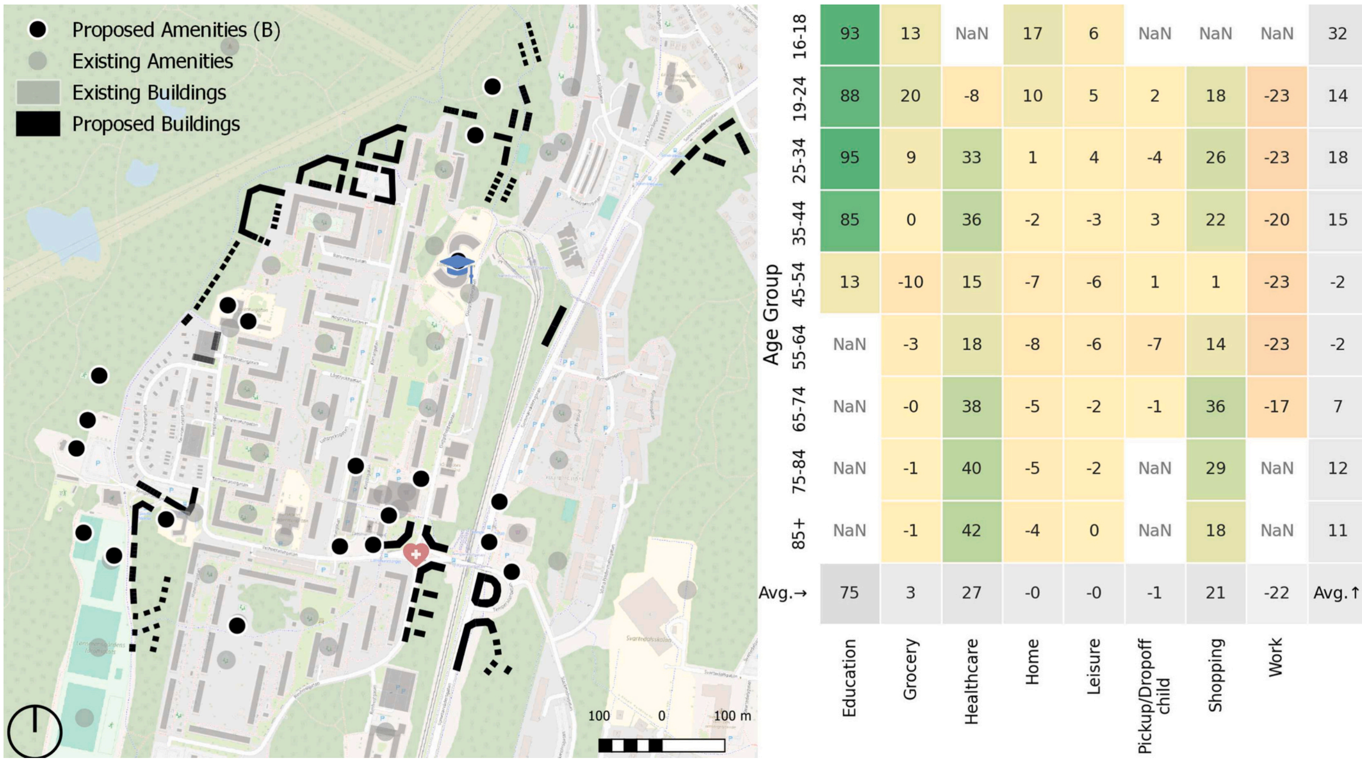

Fig. 18. **Scenario C** with the same buildings and amenities as Scenario B (left). Relative increase/decrease in TCR for non-car trips under 15 min compared to the baseline scenario (right). TCR is the proportion of all trips that are completed under 15 min.

distribution of age and sex (see Fig. 12 for a plot of normalised RMSE values). Similar validation steps are carried out for errors in the number of cars and primary status (working, studying or neither) assigned to individuals in each neighbourhood.

Since the activity chains are assigned by sampling the NHTS, we do not perform additional validation of the cumulative activity demand due to a lack of classical calibration data, such as localised traffic volumes or a neighbourhood-level activity demand census. However, on the city level, the results from the sampling show that activity purposes of shopping, education, pickup/dropoff of children, leisure, healthcare and grocery shopping have a Normalised Percentage Error (NPE) of less than 1.5 % (see 2). Next, we compare the proportion of travel modes assigned at the city level for Gothenburg.

Next, we use the Hellinger distance metric to evaluate the similarity of travel distance and travel time distributions across different modes of travel and activity purposes (see Tables 3 and 4). The HD measure is calculated to compare the similarity of distributions from the synthetic travel behaviour to the surveyed travel behaviour. The results are within the range found in the literature and show that the proposed model produces similar distributions to those found in the survey at a city level.

Finally, we look at the median travel distances per mode and purpose. Since the model aims to impute national-level travel demand and adapt it to individual neighbourhoods, we compare the median travel distance and time for different modes of transport and activities to evaluate the destination assignment and routing.

Figs. 13 and 14 show an overlapping density plot of the median travel distances and durations between the survey and synthetic data. We chose the density plot over a histogram as the survey's reported travel durations and distances are often rounded numbers to the closest 5 or 10 min/km. The density plot smoothens over the discrete values to provide a clearer overview of the distribution. We also mark the median values using a dotted vertical line and mark the mode of the distribution using a black dot. Fig. 13 shows variations in the median distance travelled. While the model reproduced the median travel distance for car travel (the most common mode of travel with a significant share in work trips) and walking (only short distances) faithfully, it struggles to reproduce the median travelled distances for public transit and cycling, which have medium to long travel distances and perhaps more sophisticated behavioural considerations not accounted for in our model.

The synthetic dataset captures the overall shape of the distribution for unimodal distributions, while multi-modality is not captured well. For example, we see two modes in the median distance travelled for education. The first is a dense mode at a shorter distance (1.33 km), and the second is a less dense mode at a further distance (5 km). Most of the population engaged in educational activities would be school children attending destinations closer to home. In contrast, a smaller population attends high schools and universities that are limited in number. The hierarchical nature of these activities creates multiple modes in the dataset, which the model fails to capture.

The results show that the destination assignment for the different activities gives preference to the home neighbourhood of the resident. While this is true for most travel destination choices, non-grocery shopping and leisure activities do not fall into this pattern. The proposed model under-reports travel times for leisure and shopping activities since residents do not necessarily prefer to fulfil these activities within their home neighbourhood (see Figs. A2 and A3 for additional comparisons).

4.2. Application of the model

The following section describes how the proposed AcBM can be applied in practice to evaluate residents' accessibility to amenities.

We compare populations sampled from different neighbourhoods to evaluate the impact of sampling new synthetic residents from neighbourhoods. The results show little change in amenity demand while sampling from the same or nearby neighbourhood. However, we can observe changes in amenity demand when sampling from neighbourhoods further away. Compared to sampling from the same neighbourhood, sampling from diverse neighbourhoods results in a different amenity demand pattern as these neighbourhoods have a different

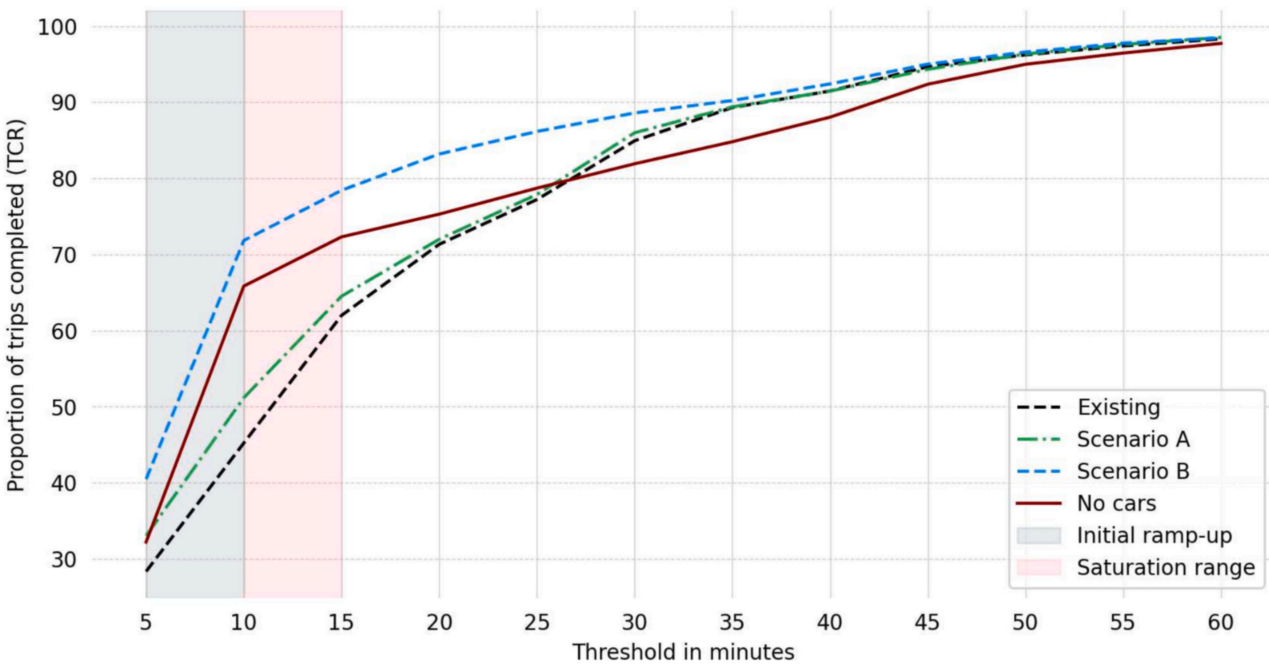

Fig. 19. Trip Completion Rate over time.

demographic composition (see Fig. A4).

Next, we present the results of the baseline and three planning scenarios. The baseline scenario includes the new residential buildings but no new amenities. Next, scenario A includes the residential buildings and a few proposed amenities (i.e. playground, preschool and shopping). Scenario B includes the residential buildings and additional amenities (i.e. playground, preschool, shopping, adult education and healthcare). Finally, scenario C, a car-free version of scenario B, is evaluated using a TCR with a 15-min threshold. All the previously mentioned scenarios are evaluated using the TCR indicator. The parameters for the TCR indicators are age group and trip purpose. The TCR indicator is evaluated against a 15-min travel time threshold. A TCR of 100 implies that all residents in that subpopulation completed their trips in under 15 min, while 0 implies that none of the residents could complete their trips in under 15 min. For the baseline scenario, the TCR is reported out of 100. Still, for the rest of the scenarios, we only report the change (increase or decrease) compared to the baseline in TCR and visualise them using different colour schemes.

Fig. 15 shows that *leisure* has the highest completion rate among all activities and age groups (84 %); next is *grocery* (80 %), followed by *home* (76 %) and *picking up and dropping off children* (72 %). Existing grocery stores and preschools in the neighbourhood and proximity to public transport stops can explain these completion rates. The lowest completion rates are for adult *education* (8 %), *work* (26 %), and *healthcare* (48 %) trips. This can be explained by the fact that for *education*, *work*, and *healthcare*, residents travel to the city centre or other specific locations for these activities, following which the trip home is generally reflexive. Due to the stochasticity in the sampling, some activity categories do not receive any trips from certain age groups; these are marked with *Not a Number – 'NaN'* in the TCR matrix.

For scenario A, Fig. 16, the baseline scenario shows the relative change in the TCR for all trips under 15 min. The first intervention proposed by the city is to respond with new preschools and shopping amenities. The most significant increase in TCR can be seen in the *shopping* category by 20 % with marginal changes across other activity categories. While all age groups benefit from the addition of shopping activities, older adults benefit most, as they are more likely to engage in shopping activities. The increase in picking up and dropping children is marginal at 2 % due to the existing preschools in the neighbourhood.

For scenario B, we investigate the addition of adult education and healthcare. Both these amenities were highlighted in the public consultation conducted by the city with the residents in the neighbourhood. They can be seen lacking in scenario A. Fig. 17 shows that residents engaged in adult education see the most direct benefit of this addition. Regarding healthcare, residents between the ages of 25 and 44 and adults over 75 see the most benefit of including a healthcare facility in the neighbourhood.

The goal of the new neighbourhood plan, however, was to promote a car-free neighbourhood where residents could access all amenities in 15 min - scenario C (see Fig. 18. Here, we see that adult education has had the most significant improvement across age groups at 75 %, followed by healthcare at 27 % and shopping at 21 %. However, travel to work experiences detrimental distributional effects. Now, the planner can use this feedback to propose alternative scenarios or social infrastructure to compensate for the reduced TCR, such as complementary bus routes or at-home services for specific demographic groups. Planners can also compare who the beneficiaries of different investments in the neighbourhood would be.

Given sufficient time, all residents will eventually reach their destinations in the above-mentioned planning scenarios. The goal of the planning exercise was to propose a scenario that provides equitable access to all residents against a normative threshold, the fifteen-minute city.

Fig. 19 shows the progression of TCR as more time is allotted in each scenario. Notably, all proposals converge to around 95 % TCR at around the one-hour mark. Over time, the TCR can be divided into two distinct phases: an initial rapid increase followed by a gradual rise. The initial phase represents the potential activities that can be fulfilled within the neighbourhood, while the gradual increase corresponds to activities that take longer to be fulfilled outside the neighbourhood.

5. Discussion

The TCR indicator addresses gaps in existing accessibility indicators highlighted in the literature. In particular, Van Wee and Geurs (2011) highlight a need for indicators of distributional effects, social exclusion, slow modes and local accessibility characteristics. The benefits of TCR in evaluating local accessibility are exemplified when combined with an AcBM of neighbourhoods. Our proposed indicators incorporate the normative perspective of spatial equity by enabling decision-makers to choose the variables they would like to examine the distributional effects of neighbourhood plans and assign a threshold to evaluate the distribution.

Fig. 17 shows that the primary beneficiaries of the new neighbourhood plan are younger and older adults who generally have lower access to cars. Planners may also consider adding a healthcare amenity in the square to improve the healthcare TCR of older residents in the neighbourhood. Still, additional considerations must be given to achieve the stated goal of a fifteen-minute city (see Fig. 18).

Using the proposed methodology, planners may ask whether 15 min is a reasonable ask from the neighbourhood in question. As shown in Fig. 19, across all the proposed scenarios, there is potential for a high number of residents to complete their trips between the 15 and 20 mark. Specifically, scenario B demonstrates over 80 % of their activities in 15 min. This suggests that it is indeed reasonable for activities to be considered within the 15-min evaluation criterion.

In scenario C, which evaluates residents who don't use cars, we observe that while the saturation point for the initial ramp-up of activities fulfilled within the neighbourhood only covers 65 % of the population, it is higher than the baseline scenario with cars.

Planners can use these comparative scenarios to formulate solutions that do not necessarily require creating new amenities. Instead, they can introduce equitable initiatives such as flexible land-use allocation and supplementary transit routes. These strategies can be tailored to particularly benefit the most disadvantaged users in the neighbourhood, ensuring more equitable access to essential services and activities.

5.1. Evidence based planning

Spatial planning is a multidisciplinary process. With the growing importance of evidence-based planning, evidence plays a vital role in acquiring the necessary political support, social acceptance and legitimacy for planning scenarios to be implemented (Davoudi, 2006; Kafkalas & Pitsiava, 2023). Using feedback from planners at the early stages of the model's development process highlighted the importance of visualising modelling results. Visualisations help planners communicate design intent to stakeholders such as policymakers and residents. Hence, the model supports a variety of visualisation types across aggregate dimensions. Our proposed method bridges the evidence gaps among the different disciplines involved in spatial planning. It integrates the collaborative and normative decision-making processes into a quantitative method to evaluate the distributional effects of planning scenarios on spatial accessibility. Additionally, practitioners could use the model to investigate where to locate new amenities and how many are needed to reach a desired TCR level. Practitioners could provide zones where specific amenities could be located and then use an optimiser to identify the location and number of amenities required to achieve a desired TCR under different conditions.

5.2. Integrated pipelines

In the AcBM literature, there is a growing interest in developing generalised end-to-end pipelines (Barthelemy & Toint, 2015; Hörl & Balac, 2021; Strobel & Pruckner, 2023) that address all the steps of an AcBM regardless of the geographical region. While this is extremely important to the development of the field and exemplifies the utility of AcBMs in applications outside of transport planning, there is also a need for models tailored to the data availability of specific regions. Even when statistical data is openly available, slight variations in the data structure can determine which methods are feasible. We encourage researchers to explore the development of generalised models but not to ignore the value in geographically tailored models that, while limited to a single region, can provide value in different disciplines. The methods proposed in this paper build on previous research on equity in accessibility modelling, such as the model by Allen and Farber (2020) and Järv et al. (2018) by developing a model of dynamic neighbourhood accessibility exemplified through a case study of a neighbourhood in Gothenburg.

5.3. Limitations

While our study provides important insights, it is not without its limitations. AcBM techniques are data-intensive, and our methodology is designed to be compatible with Sweden's current data landscape. Therefore, while the methodology is general and transferable to new regions, the data requirements in the model pipeline may need to be modified to be applied to another country. Further, we use a simplified model to generate activity demand through sampling fulfilled activities from a national travel survey. Future research should explore extending the presented method to include activity scheduling and capacity of destination amenities to look at both latent and realised travel demand. Another limitation of the proposed model is that it prefers the residents' home neighbourhood for leisure and shopping trips. While a gravity model could potentially solve these issues, the neighbourhood-centric approach of the model is desirable to achieve the aim of this research, which is to support neighbourhood planners with accessibility assessments within the neighbourhood. Users of the model for other purposes must be aware of these limitations. Additionally, researchers interested in developing the model further can investigate integrating children's activities within it. We initially explored the procedural generation of children's activities. However, we did not include them in the final model as it was not feasible to integrate dependent activities like picking up and dropping off children for parents in the same household with the current sampling approach. These research directions could further improve the robustness and representativeness of real-world activity patterns.

Compared to larger analytical models of cities, neighbourhood models require nuances one must consider as a modeller. As the spatial scale reduces, accurately representing the household becomes essential. While at the city scale, the dynamics of household composition may not matter as much if we want to capture intra-household dynamics, such as task scheduling and the impact of the BE on the ability of residents to perform dependant tasks like picking and dropping children, household composition is an important consideration in the modelling.

While the proposed model and, subsequently, the TCR indicator include the relationships between the different accessibility components by showing the distributional effects of planning decisions taken at the neighbourhood level, they can only provide a partial view of spatial equity. For example, Van Wee and Geurs (2011) describe the distinction between voluntary and non-voluntary choice. *Choice* is an exogenous component in our model, sampled or predicted from national travel surveys, and decision-makers must consider such modelling parameters while making decisions based on the model output. Compared with state-of-the-art transportation models such as MATSim (Axhausen et al., 2016), where each resident updates their destination choice based on their current location, the destination choice is made based on the resident's home location and not adjusted based on their current location. For instance, if residents wish to purchase groceries on their route back from work, our model will route them to the preferred neighbourhood grocery store rather than identify new grocery stores proximate to their current location.

A final limitation we would like to highlight is the availability of high-quality and up-to-date datasets on the location of amenities. While we use multiple data sources, both crowd-sourced and authoritative, amenities may be missing. Users of this model must be cautious when evaluating the quality of the amenities' dataset by adding any missing data.

6. Conclusion

This study aimed to investigate whether modelling techniques developed in transport and land use planning can be adapted to plan spatially equitable neighbourhoods. It addresses the gap in providing neighbourhood planners with analytical methods for understanding residents' ability to fulfil their daily needs. By adopting an activity-based approach, our research helps planners shift focus from evaluating the BE to understanding residents' interactions within their neighbourhoods by examining the distributional effects of spatial accessibility using our model.

Our findings demonstrate that by selecting suitable modelling assumptions and relevant mechanisms of how residents interact with their BE, AcBMs can capture the nuances of how residents interact with their BE. Our proposed model and the case it is applied to illustrate that AcBMs can be validated in their ability to capture demographic variations between neighbourhoods and, subsequently, the change in amenity demand. Additionally, we propose using the TCR indicator as an accessibility measure to simplify the evaluation of spatial equity for neighbourhood residents using complex data.

The use of Monte-Carlo sampling to generate ontologically coherent household relationships, combined with sampling activity chains and routing mechanisms used in our study, contributes to developing regional end-to-end pipelines for AcBMs for neighbourhood planning.

Practically, our research shows that neighbourhood planners can quantify the added value of their neighbourhood plans. Planners can compare scenarios to improve spatial equity by evaluating the distributional effects of dynamic accessibility. These implications extend to energy modelling, circular economy, deployment of charging infrastructure, and other disciplines in which there are concerns about quantifying the social consequences of design decisions at a neighbourhood scale.

In conclusion, our study contributes to a deeper understanding of how AcBMs can be used in neighbourhood planning. It highlights the need for analytical models to shift their focus from the BE alone to include the residents' perspectives.

Declaration of generative AI and AI-assisted technologies in the writing process

While preparing this work, the authors used ChatGPT to create LaTeX representations of mathematical formulas. After using this tool, the authors have reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

S. Somanath: Writing – original draft, Software, Methodology, Investigation, Conceptualization. **L. Thuvander:** Writing – review & editing, Supervision, Conceptualization. **J. Gil:** Writing – review & editing. **A. Hollberg:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors have no competing interests to declare.

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Appendix A. Appendix

Table A1

Number of closest locations considered for each activity purpose: The table shows the number of closest locations considered for each activity type. For each resident, the model identifies the origin of their home and creates a pool of considered locations by proximity. The closest *n* destinations that satisfy the activity demand are pre-calculated. Then, a location is selected randomly for the given activity. For education related to younger children, the pool of amenities is small. As the age groups increase, the pool of amenities is larger. For *shopping-other, leisure and healthcare,* the model is allowed unrestricted access to the entire city and can be randomly picked. This behaviour can be modified based on the application of the model.

Activity Purpose	Number of Closest Locations Considered
EDUCATION_förskola	4
EDUCATION_förskoleklass	4
EDUCATION_grundskola	10
EDUCATION_gymnasieskola	10
EDUCATION_fritidshem	4
LEISURE_sports	20
LEISURE_playground	20
EDUCATION	10
SHOPPING_OTHER	Unrestricted
SHOPPING_GROCERY	Handled by gravity model
WORK	Handled by gravity model
LEISURE	Unrestricted
HEALTHCARE	Unrestricted

Table A2
Mapping of NHTS Activities to OSM Amenity Tags (Top 10 Tags per Activity): The table shows the OSM amenity tags mapped to the NHTS activities to obtain a list of total amenities in Gothenburg. A complete list of OSM tags was first identified by downloading all amenities for the Gothenburg region using the OSM API. Then, a list of unique tags was created and manually categorised to create the mapping. In total, over 60 amenity tags were categorised.

Activity	OSM Amenity Tags
EDUCATION	school, educational_institution, college, university + Locations from Gothenburg city school portal
HEALTHCARE	hospital, dentist, clinic, doctors, pharmacy
LEISURE	beach, fitness_centre, marina, swimming_pool, escape_game, skatepark, picnic_table, sports_centre, bird_hide, zoo
LEISURE_PLAYGROUND	playground
LEISURE_SPORT	fitness, swimming, soccer, tennis, judo, skateboarding, yoga, climbing, basketball, scuba_diving
SHOPPING_grocery	supermarket, frozen_food, health_food, convenience, greengrocer
SHOPPING_other	clothes, electronics, florist, books, bakery, jewellery, shoes, hairdresser, computer, furniture

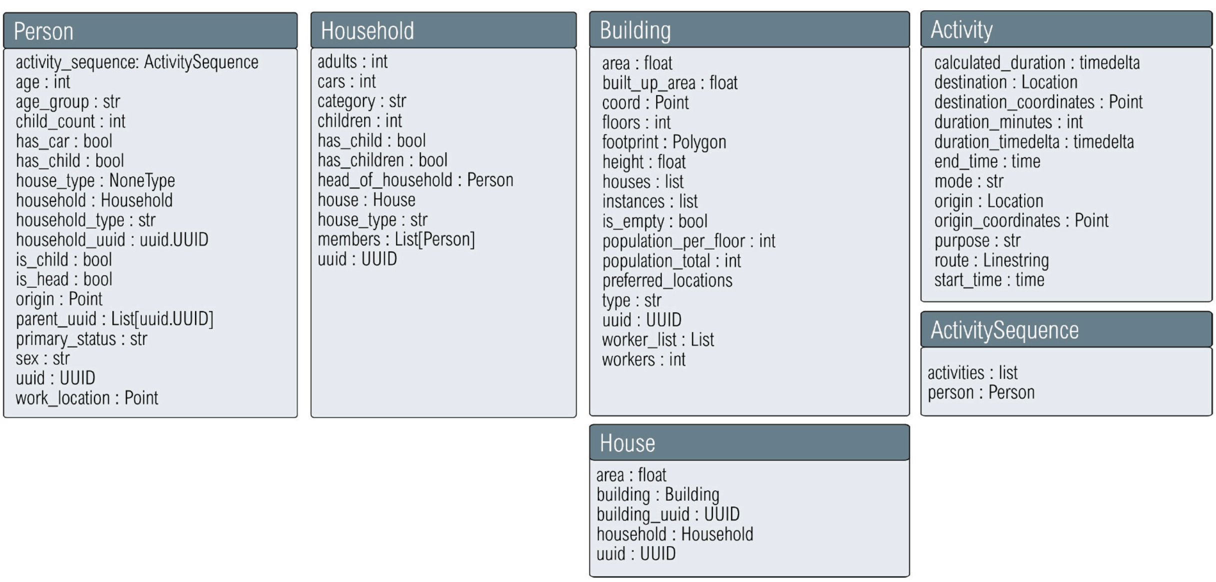

Fig. A1. Synthetic entities created within the model: The figure shows an overview of the different entities implemented within the model. The model defines six main entities: person, household, house, building, activity and activity sequence. A person represents an individual above the age of 17 that belongs to a household. A household may contain different individuals that may or may not be related. Relations within the household may be between a parent-child or a couple. A household resides within a housing unit that is, in turn, contained within a building. The building entity is linked to existing buildings in Gothenburg. However, proposed buildings may also be added. Finally, an individual is assigned an activity sequence comprised of a list of activities that outline where, when and how the individual travels for an activity.

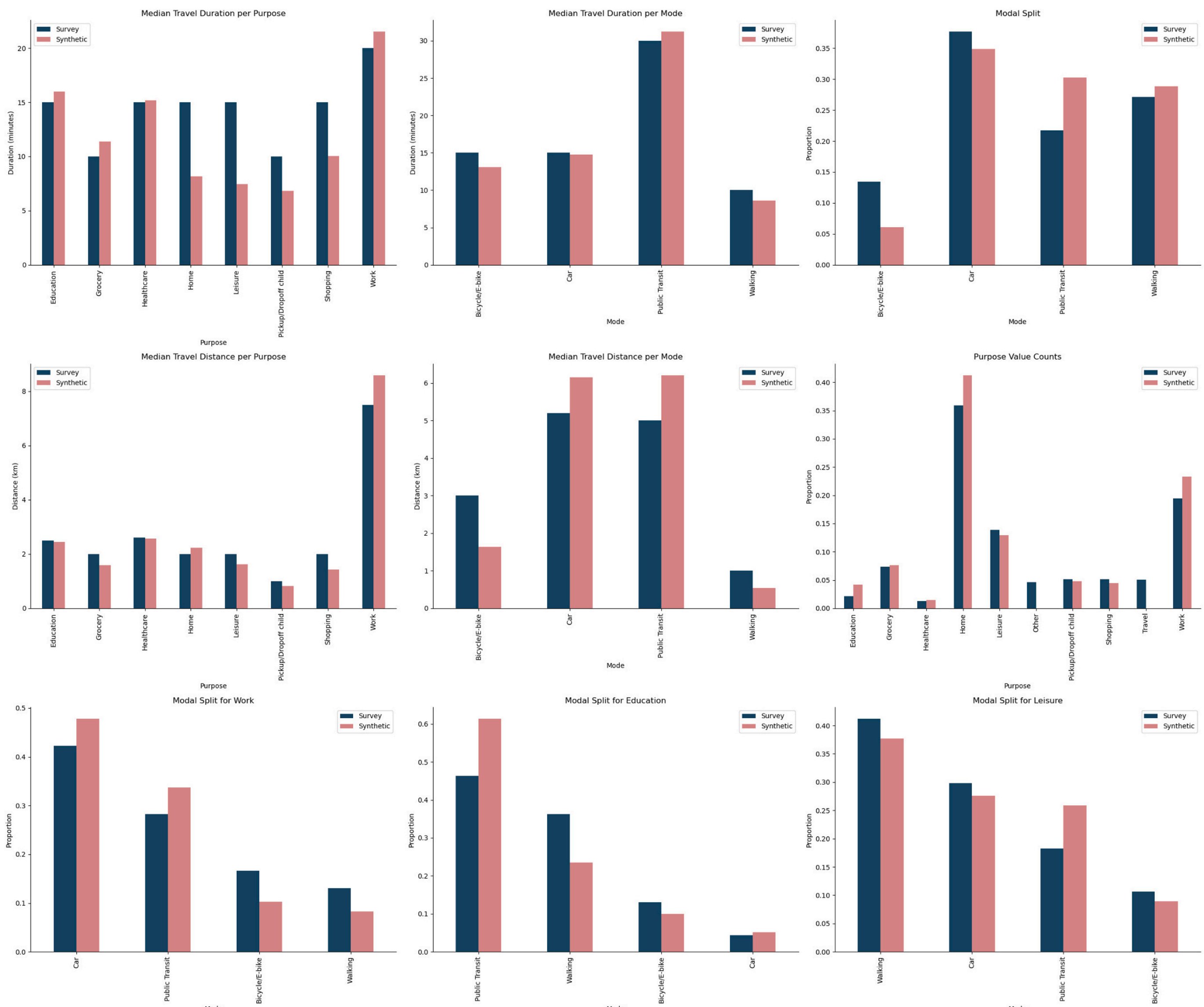

Fig. A2. Summary plot of different evaluation parameters: The figure shows 9 plots comparing the surveyed and synthetic population across median distance and duration, proportions of mode and activity purposes and the modal split for the three largest activity purposes: Work, Leisure and Education.

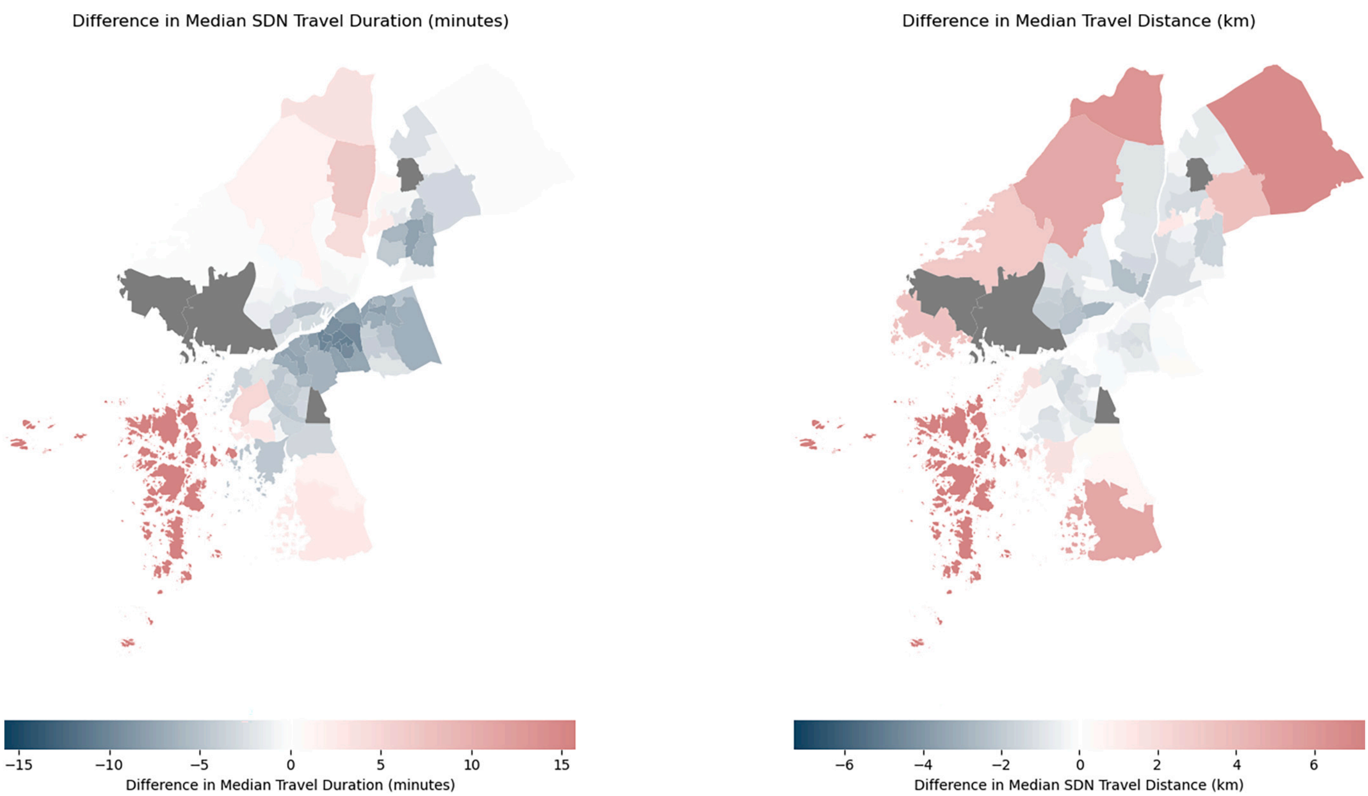

Fig. A3. Difference in median travel duration and time per neighbourhood as compared to the SDN median: The SDN is a larger administrative boundary that covers several neighbourhoods. Gothenburg is divided into 5 SDNs: North, South, East, West and Central. The NHTS data contains the SDN to which the resident belongs. We calculate median travel times per SDN and plot the difference using this data. Neighbourhoods on the city's outer areas and the islands have larger deviations from the median SDN values.

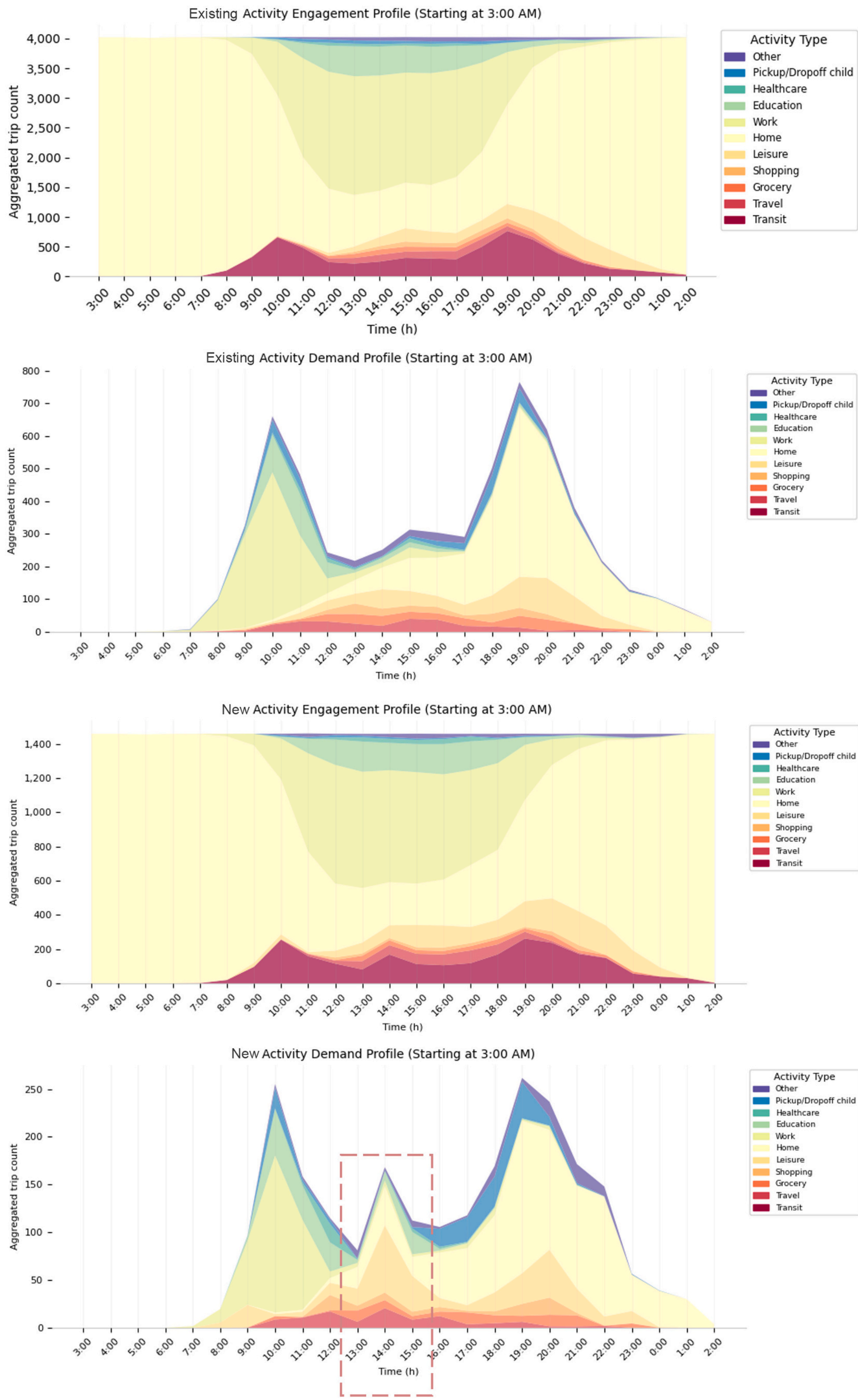

Fig. A4. Comparing the baseline amenity demand to the amenity demand of new population moving into the neighbourhood: Compared to the residents from the existing neighbourhood, there is an increased demand for leisure and shopping activities, while essential activities like grocery shopping do not show any significant variability.

Data availability

Data will be made available on request.

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