Towards Inclusive Urban Planning: An Elderly–Focused Agent-Based Model of West Midlands

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Summary

The UK population is ageing. This demographic trend is challenging for existing infrastructure and services because older people have specific daily activities and mobility patterns. Moreover, the older population is highly heterogeneous regarding demographics, health conditions and transportation access. While agent-based models are increasingly used in urban planning, they generally ignore this heterogeneity in elderly populations. This paper presents an agent-based model to support urban planning related to seniors in the West Midlands county, UK. The model is built and validated using mainly open data. Its potential is illustrated on the example of elderly healthcare accessibility.
KEYWORDS: synthetic population, MATSim simulation, elderly mobility, urban analytics

1 Introduction

Urban planning increasingly uses agent-based models (ABMs), acknowledged for their ability to represent heterogeneous human behaviours and decisions. ABMs represent a system as a set of heterogeneous agents, with individual attributes and behaviours, interacting in an environment. The ABM approach applied to cities can thus represent populations at a microscopic level with accurate demographic attributes and spatial locations, as well as phenomena emerging from individuals' behaviours and interactions (Crooks et al., 2021). ABMs have for instance been used to help urban planning to simulate exposure to environmental stresses (Yang et al., 2018), or to model bicycle flows and support cycling promotion (Kaziyeva et al., 2021).

A growing matter in urban planning is the consideration of older populations. Older people - aged 65 years or over - represent a significant part of the UK population and this trends will accentuate over the next years. From 19.2 % of the population in 2022, the elderly proportion is expected to reach 21.7% by 2030 and 24.8 % by 2050 (Office for National Statistics, 2019). Since seniors' daily activities and mobility differ from the general population, they are generally regarded as a single demographic group when ABMs are designed for urban planning. However, the elderly population is

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heterogeneous in its socio-demographic characteristics, health conditions, daily activities, mobility patterns and transportation needs (Carney and Kandt, 2022). While some seniors are in good health, highly mobile and can ensure their physical and social well-being, others struggle to satisfy their basic needs. Ignoring the heterogeneity of elderly populations can increase inequalities in seniors health and well-being. For example, the introduction of public transport in a residential area can improve older people's access to distant services. However, this might also foster poor land use mix in the area. If the public transport system is not designed for people with disabilities, some elderly populations will not benefit from it (Maynard, 2009) and might additionally face difficulties in finding local services. To prevent increasing inequalities, urban planning needs to consider the diverse older populations.

This paper presents an ABM to support urban planning related to older people in West Midlands Combined Area (WMCA), UK. WMCA covers the second most populous county in England, with almost 3 million inhabitants and 15.6% of seniors. However, the seniors' proportion by Middle Layer Super Output Area (MSOA) varies from 2.4% to 33.6%. WMCA is heavily urbanised, but also includes some rural areas, between Coventry and the main conurbation (Figure 1). The county is connected by road network, rail, bus and tram services, overseen by Transport for West Midlands (TfWM). We describe the design and validation of the model using primarily open data, and illustrate its potential for urban planning on elderly healthcare accessibility.

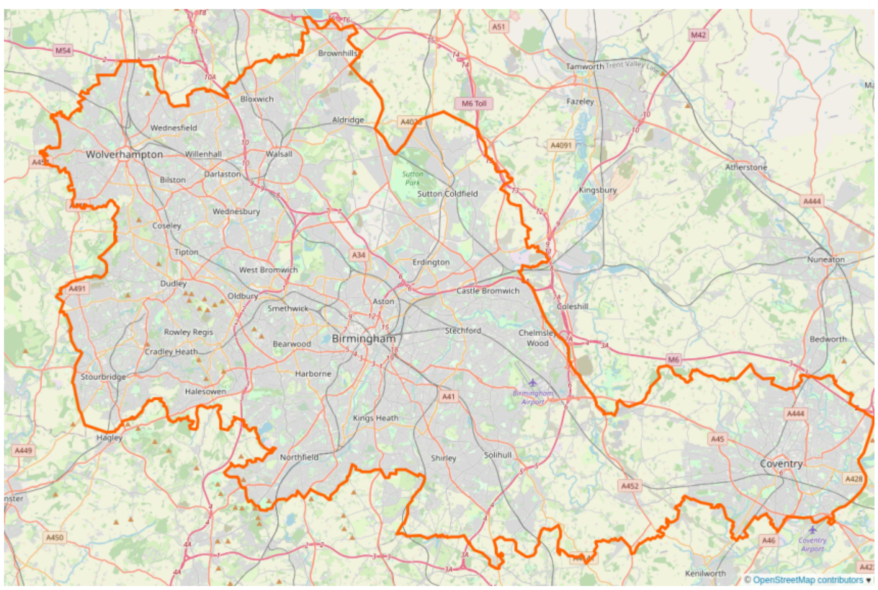


Figure 1: Screenshot of the OSM map of West Midlands County.

2 Method

The proposed ABM combines a synthetic population of agents with an activity-based model. All WMCA population is modelled - not only elderly groups - in order to reproduce interactions between individuals, i.e. in households and in the environment.

2.1 Synthetic population

A synthetic WMCA population for 2022 was generated using the open-source tool SPENSER (Lomax et al., 2022). SPENSER uses 2011 census data and population projections of the Office for National Statistics (ONS) to generate a synthetic population of individuals with age, sex and ethnicity attributes, related into households at the Output Area (OA) level.

Besides age and sex, transportation access, health status, income, occupation and qualification have also been identified as key determinants of seniors' lifestyles (Carney and Kandt, 2022; Luiu and Tight, 2021). We then used an open source extension of SPENSER (Alvarez Castro and Ford, 2022) to supplement synthetic individuals with additional attributes. Attributes were assigned probabilistically according to age and gender distributions from census and ONS regional data.

The 2022 synthetic population is composed of 2,937,639 agents, including 444,507 seniors, each with 21 attributes related to their socio-demographics, household, transportation access and residential geolocation (Figure 2).

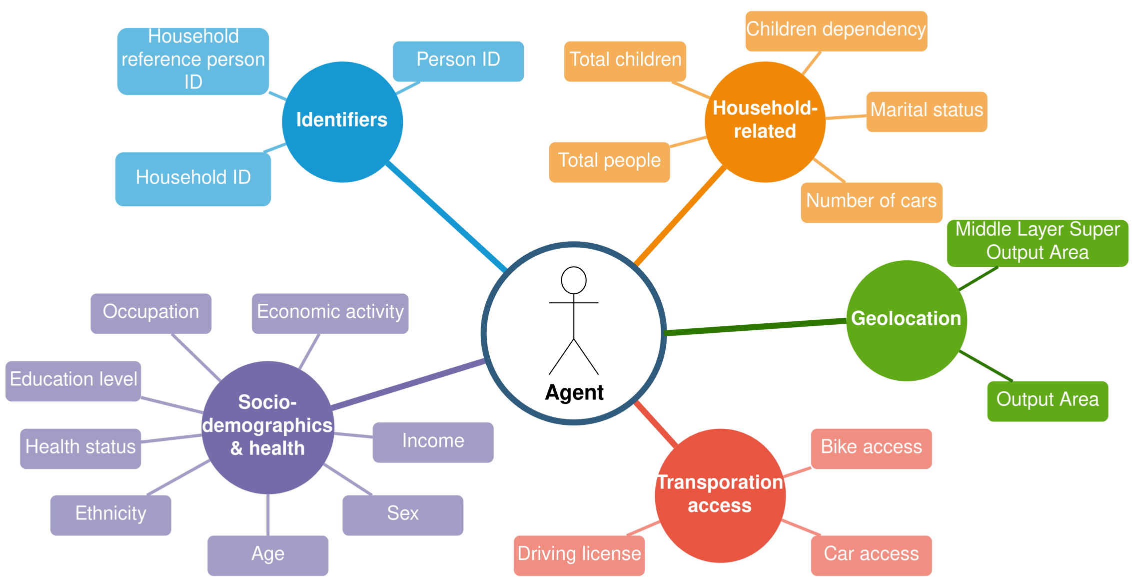


Figure 2: Synthetic population attributes.

2.2 Activity-based model

An activity-based model simulate individual trips over a day or a week. In such models, the travel demand is derived from people's activity schedules, which allows a fine modelling of individuals' decisions and behaviours. Agents were assigned weekly plans using National Travel Survey (NTS) microdata from 2018 and 2019 (pre-COVID years). NTS is a household survey on people travel and factors affecting travel, and microdata contains demographics and weekly schedules of individuals.

An unconstrained statistical matching algorithm was used to match each synthetic individual with one of the 23,888 individuals from the 2018-2019 NTS records (see Namazi-Rad et al. (2017)). Each agent was matched to its nearest NTS neighbour using a ball-tree structure and Manhattan distance on their common attributes, i.e. sex, age range, health condition, income range, economic activity, qualification, driving license, bike access, car access, household size, presence of children, marital status, and rural/urban residential area classification.

At the end of the process, each agent is associated with a NTS record and its weekly plan of activities. Each activity is defined by its start time, duration, purpose (home, work, education, shopping, medical, eat out, social, entertain, exercise, escort someone) and transportation mode to get to the activity (car, ride, public transport, walk, bike), as illustrated in Figure 3.

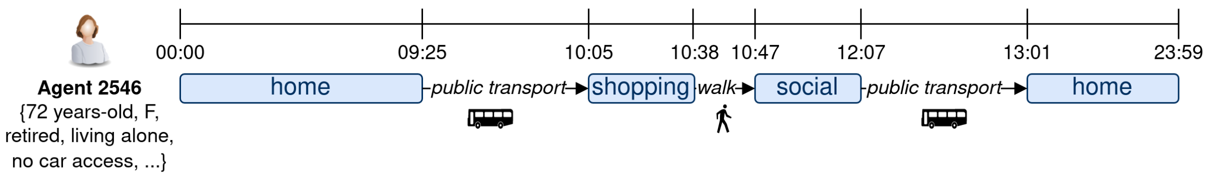


Figure 3: Example of individual daily plan.

2.3 Environment model

The WMCA road network, public transport network, as well as buildings and facilities were extracted from OpenStreetMap OpenStreetMap contributors (2017), as shown on Figures 4 and 5. Public transport stops, vehicles and schedules were modelled using GTFS data from TfWM API. Facilities from OpenStreetMap were used to assign residential buildings to households, and activities locations to agents, based on the activity purpose and trip distance from NTS data.

3 Validation and simulation

The proportion of older people by MSOA in the 2022 synthetic population reproduces well proportions reported by 2021 census, as shown in Figure 6. As they age, elderly populations become more prevalent far from urban centres, which is well reproduced.

18,148 NTS individuals were matched to the 2,937,639 agents (4,727 NTS individuals to 444,507 senior agents). An evaluation of seniors matching (Table 1) shows that more than 98% of senior agents are perfectly matched regarding sex, economic activity, driving license ownership, car access, bike access, and child presence in the household. More than 70% of senior agents are perfectly matched on health, qualification and marital status. Additional evaluation have shown that 64.9% of senior agents are matched on age within a 5-year error and 83.2% within a 10-year error. The matching is less precise but still relevant regarding household sizes, income range and rural/urban residential area classification. The total population matching scores are comparable to those of seniors.

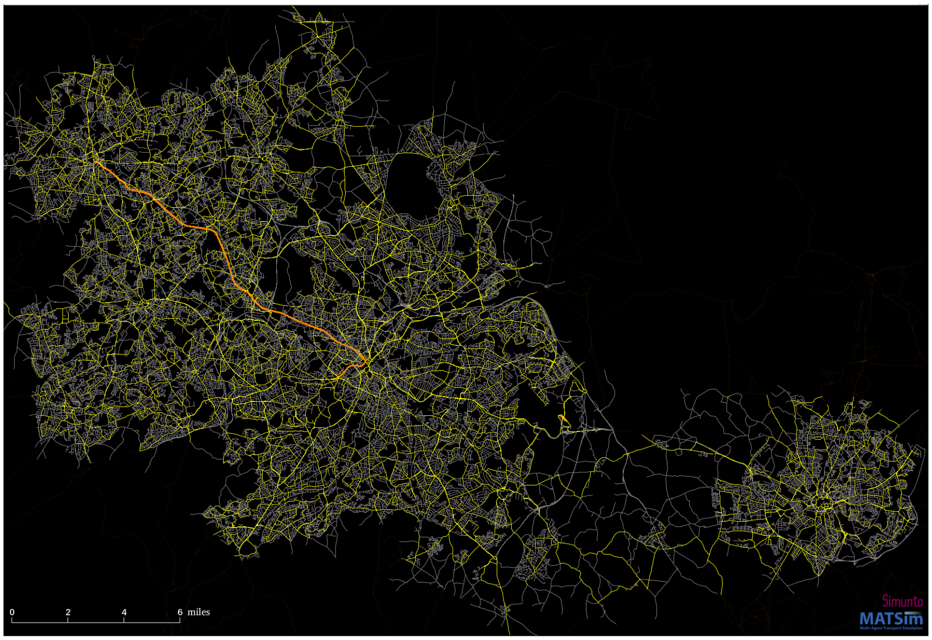


Figure 4: Model of road network (grey) and public transportation network: buses (yellow) and tramway (orange).

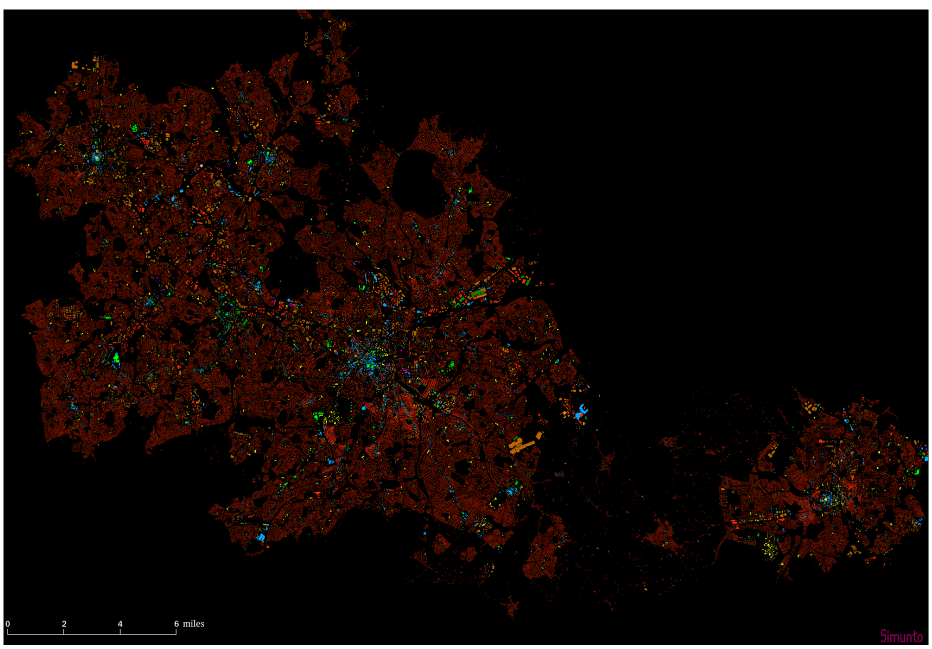


Figure 5: Model of buildings and facilities. Residential buildings (red), buildings related to shops (blue), education (yellow), transport (orange), healthcare (green), entertainment and sport (pink).

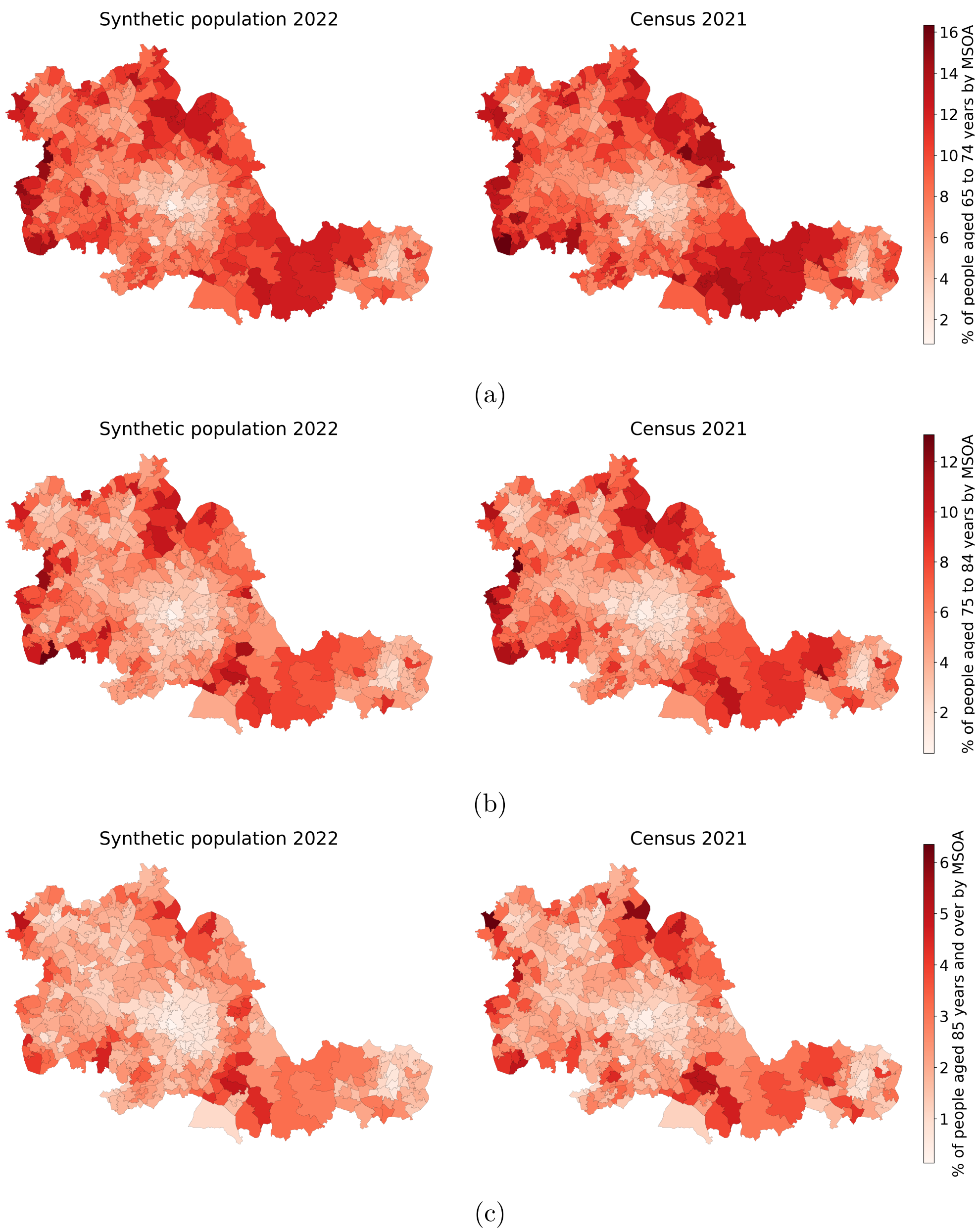


Figure 6: Proportions of older people by MSOA in the 2022 synthetic population (left) and in 2021 census (right) for age ranges: (a) 65-74 year-old, (b) 75-84 year-old, and (c) 85+ year-old.

The proposed model served as an input to MATSim, an open-source framework for ABM transport simulations. MATSim uses an utility maximization evolutionary algorithm to produce a realistic demand, finding traffic equilibrium as agents adapt their behaviour to the transport environment. Each day of the week was simulated for 750 iterations with 10% of all agents due to MATSim

Table 1: Statistical matching scores for seniors in bold, and total population in brackets

Attribute	Ordered classes used for the statistical matching	% of agents perfectly matched	% of agents quasi perfectly matched i.e. max one class shift
Sex	{f, m}	**99.92** (99.78)	-
Age range	{0-4, 5-10, 11-16, 17-20, 21-29, 30-39, 40-49, 50-59, 60-64, 65-69, 70-74, 75-79, 80-84, 85+}	**49.31** (55.39)	**78.92** (86.08)
Health status	{very poor or poor, fair, good or very good}	**82.35** (70.73)	**99.72** (98.73)
Income range	{<10k, 10-15k, 15-20k, 20-25k, 25-30k, 30-35k, 35-40k, 40-50k, 50-60k, 60-70k, 70-75k, 75-100k, 100-125k, 125-150k, >150k}	**38.03** (56.70)	**67.22** (80.19)
Economic activity	{employed, unemployed, student, child student, looking after someone, long term sick, retired, inactive}	**99.98 to 100** (99.94 to 99.99)	- -
Qualification	{yes, no}	**77.92** (88.03)	-
Driving license	{yes, no}	**99.5** (99.3)	-
Bike access	{yes, no}	**98.29** (99.27)	-
Car access	{yes, no}	**99.95** (99.79)	-
Household size	{1, 2, 3, 4, 5, 6, 7, 8, 9, 10+}	**61.68** (61.5)	**76.07** (79.9)
Children's presence	{yes, no}	**99.53** (99.73)	-
Marital status	{single, married, couple}	**71.95** (73.68)	**80.64** (87.26)
Area classification	{major conurbation, minor conurbation, city and town, city and town sparse, town and fringe, town and fringe sparse, village, village sparse, hamlets and isolated dwellings, hamlets and isolated dwellings sparse}	**66.37** (73.79)	**69.57**(78.36)

high computational cost. This includes 293,515 to 295,087 agents with 44,197 to 44,617 seniors (depending on the day simulated). At each iteration, a proportion of agents try a new plan by changing their transportation mode, route, or activity time, and when the iteration ends plans are scored (i.e. each plan's utility is calculated). When the simulation ends (i.e. equilibrium is reached), it ensures each agent uses its highest-scoring plan.

Distributions of simulated seniors trips' purpose, transportation mode, duration and distance are close to the distributions from 2019 NTS data, as shown in Figure 7. Small differences appear, notably the trip durations. This is partly due to the fact that even if the MATSim model is rescaled accordingly, 10% might be insufficient to fully reproduce congestion patterns.

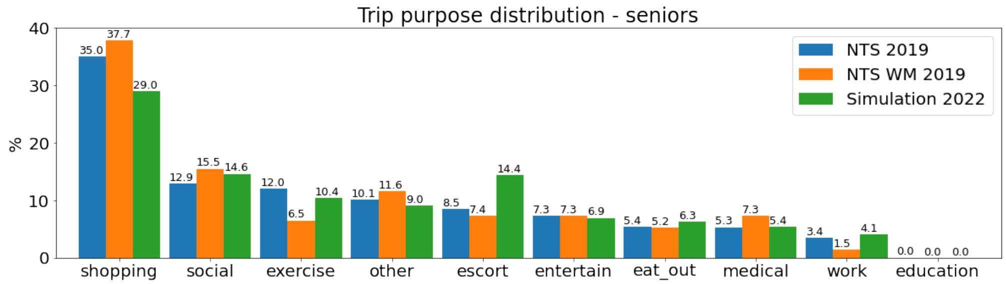
To illustrate the model's potential, we analysed simulation outputs regarding elderly healthcare accessibility. Results suggest than the mean distance travelled to healthcare facilities decreases with age, from 7.3 miles for the 65 year olds to 4.8 miles for the 85+. This means that older people either relocate closer to healthcare facilities or go to facilities closer to their home. Given the seniors' residential locations (Figure 6) and the healthcare facilities locations (Figure 8 (a)), they might tend to use facilities closer to their home. Spatial inequalities in healthcare access thus increase with age: those who live far from amenities and those who are not able to drive have a more limited access to healthcare.

Figure 8 (b) highlights important disparities depending on seniors' residential location. Coventry has longer medical trips for older populations than other local authorities (LAs): mean distance travelled is 7.4 miles for Coventry compared to [6;6.3] miles in other LAs. This is consistent with 2019 NTS data on travel time for hospitals (Table JTS0406), which shows that Coventry has the poorest healthcare access in WMCA. Simulation outputs presented on Figure 8 (c) suggest that seniors' healthcare access inequalities are even more accentuated when considering 75+ seniors (mean distance is 7.7 miles for Coventry compared to [5;5.7] miles elsewhere) and 75+ seniors without car access (mean distance is 8.9 miles for Coventry compared to [4.5;6.4] miles elsewhere). Note that the agents activities locations are estimated from the NTS trip distances, and activities locations could be refined by considering the local infrastructure. Moreover, some trip patterns could be an artefact of the boundary chosen, i.e. real individuals can potentially access facilities outside the area.

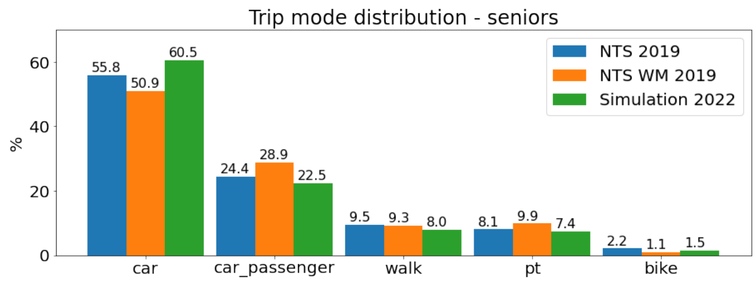
Analyses regarding other trip purposes, and other characteristics (gender, health status, household size, etc.) can be conducted with this model, to identify disadvantaged senior populations. This could facilitate the implementation of tailored local policies, e.g. introduction of a door-to-door shuttle service between some areas and major healthcare facilities.

4 Conclusion

We proposed an ABM of West Midlands population that considers elderly population heterogeneity. The model is available at `https://doi.org/10.5281/zenodo.7447094` and provides a useful tool to better understand seniors' lifestyles and mobility needs and encourage inclusive urban planning. This analysis could be applied more widely to less mobile members of society and people with physical disabilities. Future work will further assess the importance of incorporating the heterogeneity within senior populations. We will use the model to explore future transportation scenarios, such as the implementation of on-demand autonomous vehicles for senior citizens.



(a)



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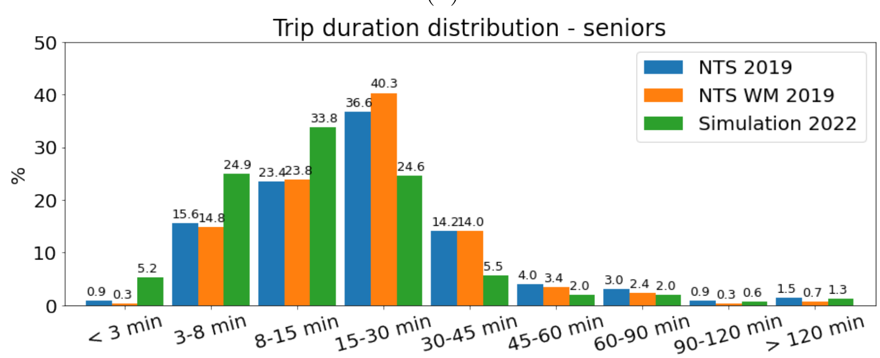
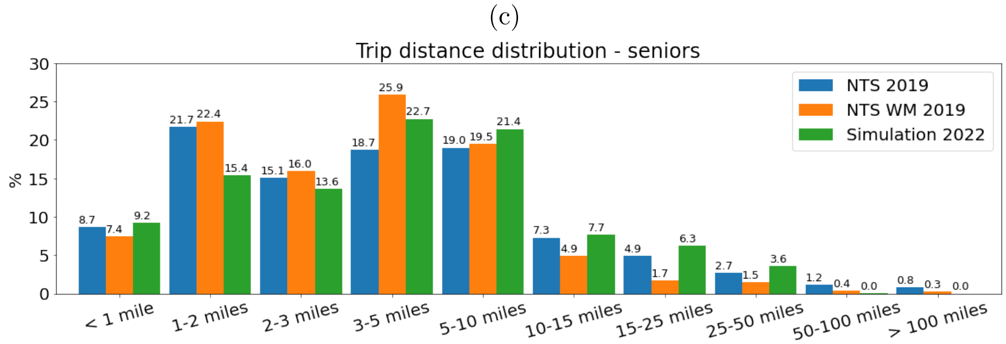
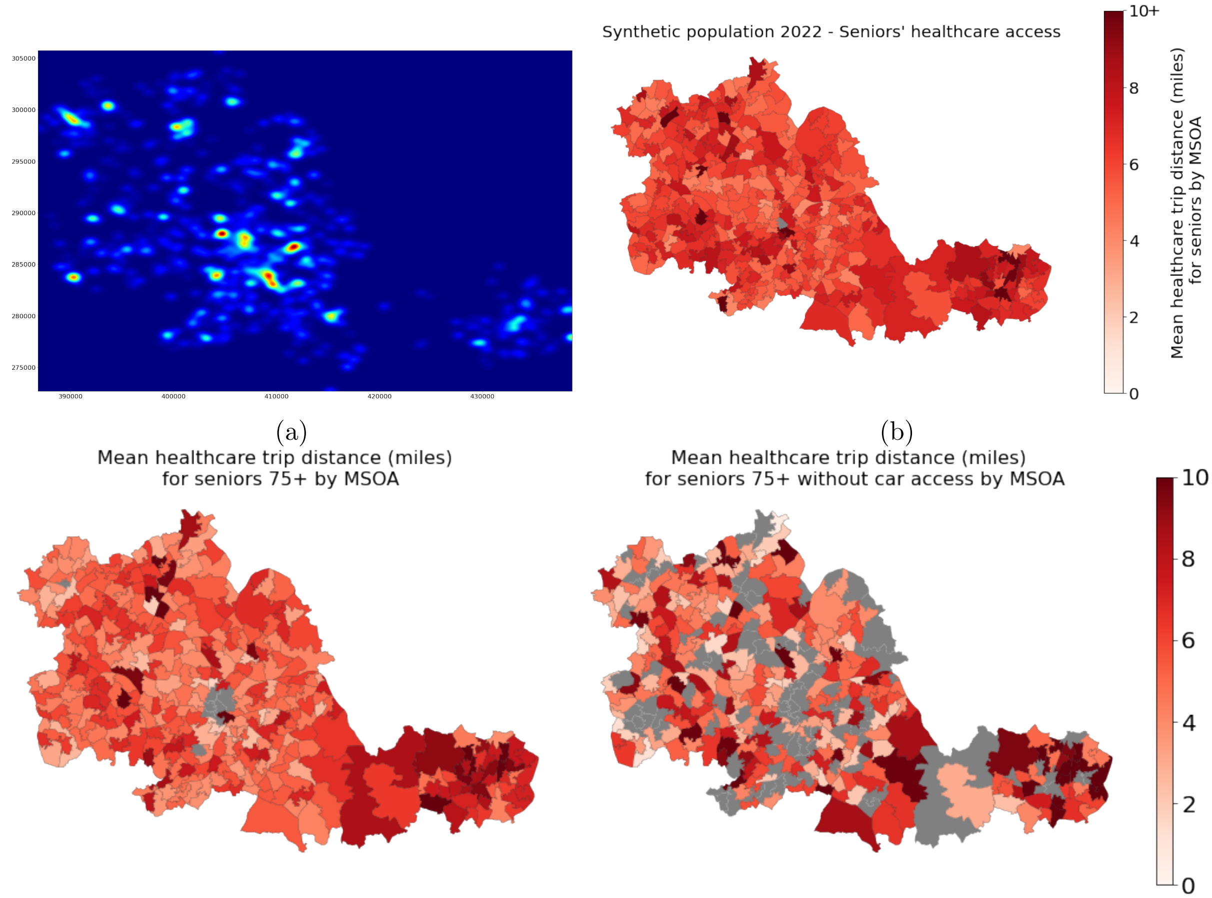


(c)



(d)

Figure 7: Distributions of simulated seniors trips' (a) purpose, (b) transportation mode, (c) duration and (d) distance compared to 2019 NTS data.



(c)

Figure 8: (a) Heatmap of healthcare facilities and mean medical trip distance by MSOA in simulation for (b) all seniors, and (c) seniors aged 75+ year-old and aged 75+ year-old without car access. MSOAs with < 3 simulated trips are shaded.

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Biography

Manon Prédhumeau is a Research Fellow at the School of Geography of the University of Leeds. Her research interest includes agent-based modelling and simulation of human behaviour, applied to urban mobility and future transportation.

Ed Manley is Professor of Urban Analytics in the School of Geography, University of Leeds, and Turing Fellow at the Alan Turing Institute. His research aims to improve our analyses and models of human spatial behaviour, and understand how these behaviours shape urban systems and public health.