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Navigating the Night: An Agent-Based Model of Nighttime Pedestrian Behaviour

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Abstract. Research in environmental psychology and safety science suggests that time of day largely impacts pedestrian spatial decisions in cities, influencing where and how people move. The cognition of the surrounding environment is altered by darkness, perception of safety, and the appeal of different routes. In this work, we present an Agent-Based Model (ABM) of pedestrian movement in cities that incorporates time-sensitive elements into the agents' route choice behavioural mechanisms by considering urban form, nighttime potential vulnerability, and the impact of street lighting. Our preliminary findings indicate that nighttime pedestrian movements differ from daily patterns. Volumes of pedestrian agents moving after sunset tend to converge along the well-known minor roads in the historical city centre. Conversely, high concentrations along rivers and in proximity to parks and green areas, typical of daily movement flows, do not surface during the night. The ABM, although at an initial development stage and built on the basis of a few behavioural mechanisms, constitutes a promising tool to advance knowledge on route choice behaviour and, after adequate calibration and validation, may emerge as a potential tool to support policy making.

Submission Type. model, case study, analysis.

BoK Concepts. Geocomputation, Geospatial Data.

Keywords. agent-based modelling, route choice behaviour, pedestrians, nighttime, cities, safety.

1 Introduction

Time of day greatly impacts the way pedestrians formulate routes across cities (Tong and Bode, 2022; Basu et al., 2023). During the day, pedestrians favour routes with mixed or residential land uses (Rodríguez et al., 2015), enjoy strolling across parks or surrounded by natural features. At night, instead, due to changes in perception of safety, they avoid poorly lit areas, vacant spaces (Basu et al., 2023), or unfamiliar locations (Svechkina et al., 2020): streets that look appealing during the day become unattractive or even frightening after sunset (Chen and Shin, 2020; Burattini et al., 2025); trees protecting strollers from the sunlight and high temperatures in the afternoon turn out to block street light and make the path unsafe at night (Rahm et al., 2021).

Environmental psychologists have devoted quite some attention to the role played by darkness in shaping the perception of the external environment. Not only does low visibility lead to an increased sense of vulnerability (Martin, 2006; Yannis et al., 2020), but it also conceals potential hazards, heightens the risk of accidents and crime, and prevents pedestrians from crossing certain areas (Boyce et al., 2000; Peña-García et al., 2015). The perception of safety during nighttime becomes a critical element in relation to route choice behaviour and urban walkability (Basu et al., 2022; Zhu et al., 2023), especially for members of vulnerable groups such as youth or elderly individuals, women, or ethnic minorities (see: García-Carpintero et al., 2022; Rišová and Sládeková Madajová, 2020; Chalfin et al., 2022). Ultimately, poorly lit or isolated areas prompt pedestrians to alter their routes or resort to alternative modes of transport (Fotios et al., 2019; Mattsson et al., 2020).

In recent years, agent-based simulations have been developed to observe how variations in the behavioural mechanisms of (pedestrian) agents bring about different movement flows across the street network of a city (Filomena et al., 2022; Wolpert and Omer, 2025). Despite a growing degree of realism in recent ABMs, however, work in quantitative geography, Geographic Information Science (GIS), and computational urban analysis has not incorporated the impact of time of day on pedestrian analysis and modelling. This makes it difficult, on the one hand, to assess the combined effect of urban form and time of day on route choice behaviour (*micro-level* scale), and, on the other hand, to observe how individual responses to different levels of perceived safety may impact pedestrian movement flows in cities at a *macro-level* scale.

In this paper, we present an ABM for simulating pedestrian movement in cities that accounts for the impact of time of day on route choice behaviour. By combining existing research on the role of i) urban form and ii) perceived safety at night in shaping route choice behaviour, this paper provides an initial attempt to generalise research in environmental psychology on the effect of light on pedestrian movement in cities. The ABM is tested for the city of Torino (Italy) and evaluated in relation to the differences between pedestrian volumes at night and during the day. Our ABM aims to position itself as a tool that can be adopted to identify areas where pedestrian volumes present higher variations compared to daytime, thereby highlighting urban areas that may require attention to make pedestrians feel safer after sunset.

2 Methods

2.1 The ABM functioning

The ABM allows exploring the distribution of agents formulating and traversing routes between their homes and destinations in the urban environment during day- and night-time, i.e., *pedestrian volumes* across the street network. In the model, *agents* represent pedestrians and are categorised as either vulnerable or non-vulnerable. Vulnerable individuals refer to people who might feel more threatened in low-light conditions. Each agent is assigned a home place, a random residential building, and a work place, a random mixed-use building. The *environment* includes a graph representation of the walkable street network, across which agents move; each street segment includes attributes pertaining to its lighting conditions and hierarchical classification (i.e., primary, secondary, tertiary, residential, pedestrian road, etc.) and its membership to one of the city's districts. Districts are identified from the configuration of the street network with community detection techniques (see: Filomena et al., 2020). Lastly, the environment incorporates geographic representations of parks, green areas, waterbodies, building footprints and their land uses.

Pedestrian dynamics are modelled by setting a daily allocation of kilometres to be walked (*K*) (see: Althoff et al., 2017) by the agent population, throughout the day. To mimic a simple activity-based design of the model, the daily allocation *K* is distributed across time intervals to reflect variations in movement patterns. Every 20 minutes, a random subset of agents is determined by dividing the kilometres allocated for that interval by an average Euclidean *base distance* (d) between the origin and the destination (OD)[1]; agents who have walked fewer kilometres are prioritised. Once selected, each agent is allocated an Euclidean distance (d_a) obtained by applying a random factor ($\pm 30\%$ range) to the base distance *d*. Finally, d_a is used to identify a random destination node with a comparable distance from the agent's home location (see Diagram 1 for a summary).

When an agent is set to walk, it i) identifies a random destination to be reached from its home place, ii) formulates its route (see below for details), iii) walks towards the destination and spends a certain amount of time there. Eventually, it formulates a route to walk back home. Every time an agent approaches a street segment, the model updates the pedestrian counts, recording them as either day- or night-time volumes (after 6 PM, before 5:30 AM, "autumn" scenario).

Algorithm 1 ABM initialisation

Input : GIS Spatial layers (GIS), general parameters
Output: Pedestrian volumes (day- *vs* night-time)

Initialize:
Load GIS features and attributes; build graph.
Set number of repetitions (jobs) and number of days.

foreach *Street segment* **do**
- Mark it as *lit* or *non-lit*.
- Assign road classification and district.

foreach *Job* **do**
- Initialize agent population A.
- **foreach** *agent* **do**
  - Classify as vulnerable or non-vulnerable.
  - Assign home- and work-place.
  - Create cognitive map.
- **foreach** *Day* **do**
  - **Define daily walking quota *K*:**
  - Peak hours $\rightarrow 0.55$.
  - Off-peak hours $\rightarrow 0.44$.
  - Night $\rightarrow 0.01$.
  - Run simulation step (see *Algorithm 2*).
  - Save daily volumes.

2.2 Agent cognition and behavioural mechanisms

The agents are equipped with a *cognitive map* that contains information about natural features such as parks and waterbodies, distribution of potential destinations, primary and secondary roads across the entire city, and their attributes. It also includes knowledge about *known districts* and their corresponding street segments; these familiar ar-

[1] Empirical contributions (see: Minardi et al., 2022; Fonseca et al., 2022) show that the average duration for a single walking trip in Italy can be estimated to be around 20 minutes; assuming an average pace of 4.5 km/h, this results in a *walking* distance of around 1500 m, ~1300 m Euclidean distance.

eas include the districts of the home- and work-places, as well as the districts forming the city centre, assumed to be known by most of the population. Furthermore, agents are able to perceive the rough number of other pedestrian agents walking on the street segment they are traversing at a certain time.

The agent's route choice behaviour follows a basic hierarchical structure that encompasses a prospective planning phase and a situated prospective planning phase emerging from the environmental information stored in its cognitive map (see Diagram 2). The *prospective* phase involves determining the route between a given origin and destination (OD) pair prior to the agent starting walking. Both during day- and night-time, agents generate routes by minimising road distance. The Dijkstra's algorithm is used for this purpose (Dijkstra, 1959) but, to account for cognitive factors in distance estimation (Manley et al., 2021), the road cost i_e of a street segment e is modelled as:

$$i_e = cost_e * Z_d \qquad with\ Z_d \sim N(1.0,\ 0.10) \tag{1}$$

where $cost_e$ is the actual cost (i.e., road distance) of the segment; Z_d is a normal distribution with a mean of 1.0 and a standard deviation of 0.10. Exclusively during the day, when a segment lies within parks or along water bodies (e.g., rivers), Z_d is a normal distribution with a mean μ_n and a standard deviation σ_n:

$$Z_d = \min(N(\mu_n, \sigma_n), 1.0) \tag{2}$$

Here, μ_n is set to 0.15, σ_n to 0.10. This has the effect, in a nutshell, of considering segments in proximity to pleasant natural areas more likely to be chosen, in line with research on people's preferences for such environments (for a short review and justification: Filomena et al., 2020). In contrast, when planning routes during the night, vulnerable agents adopt a different prospective approach: sections through parks, along rivers or waterbodies (likely to be dark), or across unknown areas, are disregarded and therefore avoided; a readapted version of Dijkstra's algorithm is used in this case.

The *situated* phase refers to potential spatial decisions along the route that might alter the original plan. In our ABM, agents take situated decisions only during night-time. Poorly lit, unfamiliar, isolated or empty streets become critical locations after sunset, even for non-vulnerable individuals. When agents prospectively plan their route, they do not fully take into account these conditions (apart from a few cases), as it is assumed that they do not hold complete information on whether a certain street may be crowded, not lit, or well-known. When walking along the route, however, as they become aware of the characteristics of the streets ahead of them, they may restructure their path, i.e., recompute the route, avoiding a segment perceived not to be safe. Under these circumstances, the model makes use of the A* algorithm (Hart et al., 1968) from the current position of the agent to the destination node; for computational convenience, the algorithm disregards segments that are considered to hinder the agent's perception of safety, based on its properties.

Algorithm 2 Simulation step

```
foreach Step do
    if Step is a 20-min time interval then
        Define a subset of agents to walk part of the quota K.
        Prioritise agents with lower walked distance.

        foreach Selected agent do
            Assign a random Euclidean distance d_a = d ± random(0.3) * d.
            Select destination ~ d_a from home-place.

    Prospective planning phase:
    foreach Agent with a destination, but no path do
        Generate route with Dijkstra algorithm.
        if Day-time then
            Prefer segments within parks.
            Prefer segments along waterbodies.
        else
            if Vulnerable then
                Disregard unknown areas.
                Disregard parks or waterbodies.

    Situated planning phase:
    foreach Agent with a destination and a path do
        Start or keep walking along the given path.
        while En route do
            if Approaching a new segment then
                if Night-time, see rules in Table 1 then
                    Do nothing OR
                    Increase Speed OR
                    Alter the initial route with A* and exit.
                Enter the segment.
                Update the previous and new segments counts.
            else
                Keep walking along the assigned segment.

        if Arrived at destination then
            Wait.
            Set the home-place as the new destination.
```

The set of situated actions associated with different lighting and location-based conditions are reported in Table 1. These were derived from the body of existing empirical research. To mention a few: pedestrians choose to move more quickly in unfamiliar or dimly lit locations to avoid spending as much time in what they consider it to be a hazardous environment (Fotios et al., 2019; Basu et al., 2022) - *Condition 3 and 5*. They also tend to steer clear of dimly lit and unsightly streets at night Boomsma

Table 1. Adaptive situated actions potentially taken by the agents when walking along a route between an OD pair, depending on lighting, location-based conditions, and the agents' vulnerability. When altering the route, agents deviate from the initial plan from their current location onwards. *In brackets decisions that have already influenced the initial Prospective Planning (PP) phase.*

Conditions	***Lit***		***Non-lit***	
	Non-vulnerable	**Vulnerable**	**Non-vulnerable**	**Vulnerable**
1. Street segment is unknown, not a main road, and not crowded	-	Alter initial route	Alter initial route or increase speed	Alter initial route
2. Street segment is known, not a main road, and not crowded	-	Alter initial route or increase speed	-	Alter initial route or increase speed
3. Street segment is a main road but not crowded	-	-	-	Increase speed
4. Street segment within a park or along a waterbody	Alter initial route or increase speed	(Avoided in PP)	Alter initial route	(Avoided in PP)
5. Street segment is unknown, not a main road, but crowded	-	-	Increase speed or do nothing	Increase speed
6. Unknown districts	-	(If possible, avoided in PP)	-	(If possible, avoided in PP)

and Steg (2014). This is particularly true for women and other vulnerable groups (Chalfin et al., 2022; Rišová and Sládeková Madajová, 2020) - *Condition 1 and 2*. Pedestrians may also feel anxious in unknown locations and roads because of a low degree of familiarity with safe spots (Phillips et al., 2013) - *Condition 6*. Furthermore, trees and vegetation may create dark spots, thus resulting in raised levels of uncertainty, even in well-lit spaces (Chen and Shin, 2020). Because of this, pedestrians are more inclined to stay away from certain areas, preferring bright streets (Rahm et al., 2021) - *Condition 4*. Finally, at night, people generally tend to favour crowded and busy locations, as the presence of others can deter crime and prompt a feeling of safety (Ferraro, 1995) - *Condition 2 and 5*. In this sense, in our ABM, a street segment is considered crowded and therefore safe to walk when the number of agents on that segment is equal to or greater than the agent count at the 20th percentile of all the non-empty street segments at that time.

2.3 Evaluation and case study city

A single model run consisted of a 24-hours simulated day. To address the randomness entailed by the selection of the OD pairs and any stochastic function of the ABM, the model was run for 42 days, a sufficient number of repetitions to observe no further variation in the emerging patterns. For each run, *pedestrian volumes* were determined from the pedestrian counts of the street segments (median value over the model runs) and categorised either as day- or night-time. Furthermore, for each segment, we verified whether the frequency distribution of the pedestrian volumes during the day and at night across the set of runs differed significantly. The Wilcoxon test (Wilcoxon, 1945), a non-parametric version of the *t-test*, was used for this purpose with a 0.05 α *value*. To account for differences in kilometre allocation, the volumes were weighted by the total distance walked under the two conditions.

The city of Torino (Italy) was used as a case study. Torino is a major city in northern Italy, located in the Piedmont region, populated by approximately 800,000 inhabitants. The municipality of Torino has been prioritising pedestrian safety at nighttime as part of its efforts to improve urban mobility and safety for all residents[2]. While many streets in Torino are now equipped with energy-efficient, modern LED lighting to improve visibility and reduce dim spots[3], the municipality has been working to map and upgrade their public lighting system.

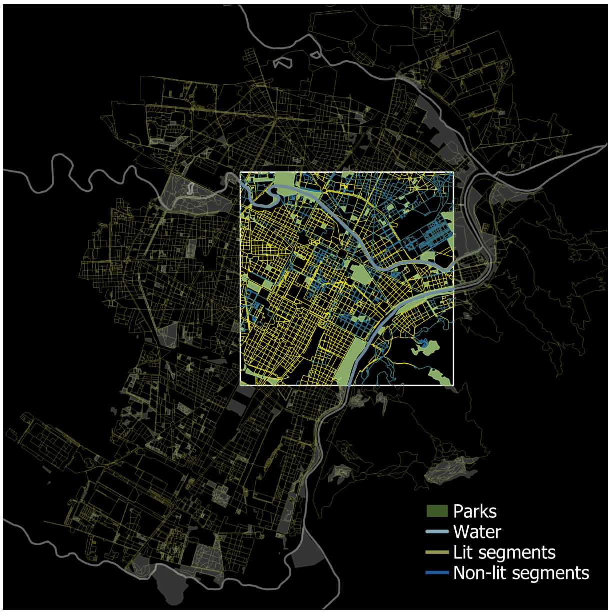

Figure 1. Torino (Italy); the study area is enclosed in the bounding box. Data source: OpenStreetMap data (OpenStreetMap contributors, 2025). The map is orientated north.

A central area of Torino, normally characterised by substantial pedestrian concentrations, was selected as the study area (see Fig. 1). It includes large transportation hubs (Torino Porta Susa and Porta Nuova railway stations), shopping areas (e.g., Via Garibaldi and Via Roma), a number of pedestrianised squares (e.g., Piazza Castello, Piazza Vittorio Veneto, Piazza Carlo Alberto), and vast parks (e.g. Parco del Valentino, Giardini Reali, and Parco Dora). The study area is also crossed by two rivers, Dora Riparia and Po', which, as separating barriers, shape the form of the

[2]https://eurocities.eu/stories/feeling-safe-at-night-in-turin

[3]https://www.aecilluminazione.com/projects/public-street-urban-lighting-city-of-turin-italy

city and people's mental imagery. The model simulated the movement of 2% of the study area's population: 16,000 pedestrian agents walking on average 4000 m per day (Althoff et al., 2017).

2.4 Data and Software Availability

The geographic layers included in the model were obtained from OpenStreetMap (OSM) (OpenStreetMap contributors, 2025). The hierarchical classification of the road segments follows the OSM classification described by the tag 'highway'. Moreover, the OSM tag 'lit' was used to determine whether a segment was indeed lit or not; null values were converted to 'lit' for main and residential roads and to non-lit, in all the other cases. On this basis, 17% of the street network of the study area is not lit (this is likely an overestimation).

The ABM was developed with GeoMason[4], an open-source Java-based modelling framework with GIS capabilities (Sullivan et al., 2010). The code of the ABM, its results, an Python scripted Jupyter Notebooks describing the preparation of the data and analysis presented in the paper are available at https://github.com/g-filomena/pedsimcityNight, under a GPL-3.0 license.

3 Results and discussion

Fig. 2 displays the pedestrian volumes generated by the ABM, i.e., not weighted with the number of kilometres actually walked during the day and in the night (the average route lengths generated during the day and at night are very similar - 1,954 m and 1,948 m respectively - but a greater number of kilometres was allocated to daytime trips). At first glance, differences between day and night appear to refer to concentrations along rivers and across parks. This is quite evident in proximity to the river Po' and its tributary Dora Riparia, as well as across and around the Giardini Reali, a park enclosed between a pedestrian square and two main arterial roads (centre of the map). While daytime volumes appear somewhat overestimated and exaggerated in some areas, others seem rather reasonable. For example, paths on both sides of the River Po' and within the parks on the sides of the river are in fact traversed daily by numerous strollers, runners, and tourists wandering in the city centre. In contrast, these waterfronts and paths are notoriously avoided at night, as most of the areas next to the river Dora Riparia. This is realistically reflected in the model results. It is worth noting that, although parks in Torino are mostly lit, they are perceived nevertheless as unsafe or dodgy areas. At night, these areas often become refuges for marginalised members of society, such as the homeless or those struggling with addiction, inducing the elderly, women, or tired workers returning home to choose other routes, unless necessary or under specific circumstances. Some footpaths and areas along the rivers present similar characteristics, and the fact that they may run at a lower level than the roads for vehicular traffic makes them even more isolated.

Fig. 3 displays a quantitative assessment of such differences. Besides the different day *vs* night patterns resulting from the mechanisms associated with natural areas, pedestrian volumes registered after 6 PM are lower (coloured in orange) in the south and centre-west of the map. There, agents seem less prone to make use of secondary roads or adopt detours they would normally follow during the day. On the contrary, minor roads in the east, towards the river Po', present higher weighted volumes (coloured in white) and appear to realistically capture the volumes normally concentrated along the river during the day. The fact that this area represents the core of the historical city centre makes us speculate that a higher number of agents would still resort to minor roads there, as these were known to the entire agent population and thus safe to be walked.

It is also interesting to see how several street segments, to some extent underexploited during the day, emerge as important lines of movement during the night. This not only relates to a more pronounced usage of primary and secondary roads but also to a general reconfiguration of the flows away from certain areas, e.g., the south-eastern corner, the north-eastern corner, and somewhat the area in the centre of the map. As mentioned above, however, some of the patterns generated by the model, e.g., the north-western sections of the paths along the river Dora Riparia exhibit unexpected daytime volumes of pedestrian agents; it is unlikely to see these portions of pedestrians in those areas in reality, as they are far from the lively city centre and predominantly residential.

4 Conclusion

Time of day entails different lighting conditions and, in turn, different spatial decisions being taken by vulnerable and non-vulnerable pedestrian agents across the city. In this paper, we defined a set of behavioural mechanisms derived from a wealth of empirical contributions in environmental psychology and safety science. We derived a novel route choice behaviour framework that regulates the formulation of paths at nighttime by considering the interaction of psychological, urban form, and social factors. Although most of the differences in patterns resulting from the behaviour of 16000 agents in the city centre of Torino (Italy) appeared to be due to the role of natural barriers in attracting pedestrians (or not), the patterns that emerged from our analysis reinforce the idea that spatial decisions in cities are not only shaped by the structural or configurational component of urban form (Wozniak et al., 2025).

Our model presents several limitations. Methodologically, not only should the ABM accommodate a larger number of agents, but it should also be validated with observational data. In this direction, although rare, large datasets describing pedestrian distributions in cities would support

[4]https://cs.gmu.edu/ eclab/projects/mason/extensions/geomason/

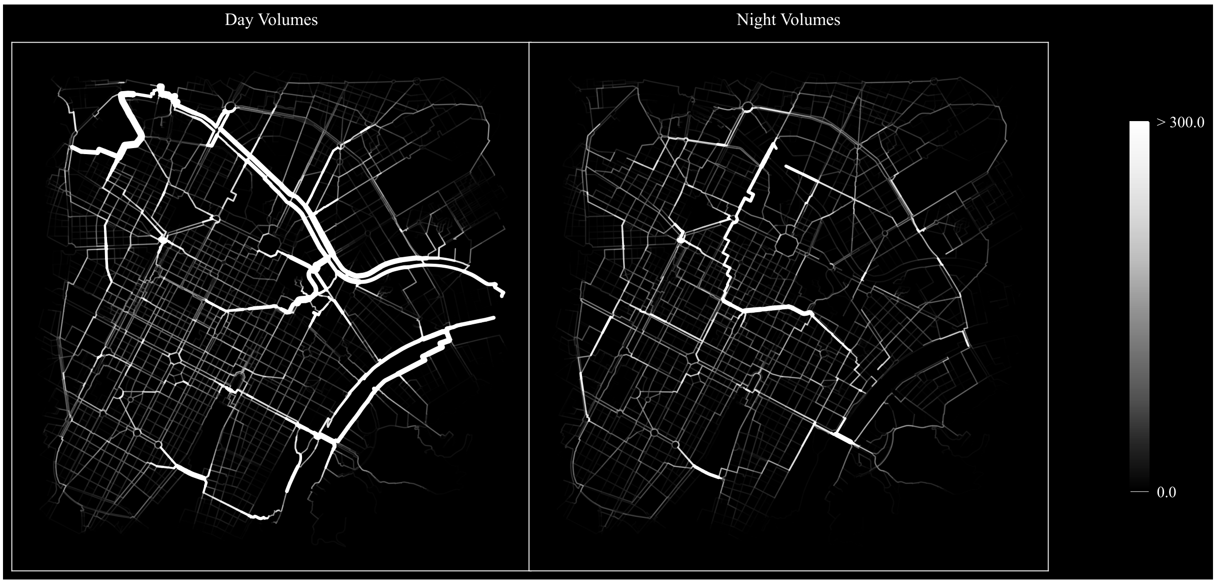

Figure 2. Unweighted pedestrian volumes resulting from the routes walked by agents during the day (left) and the night (right). Volumes are median values over the model runs.

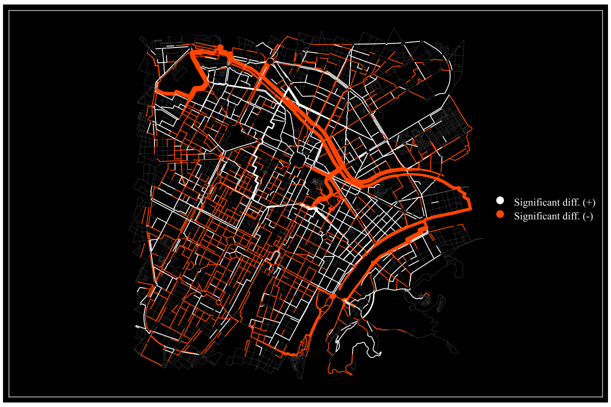

Figure 3. Statistically significant differences in volumes of pedestrian agents walking during the day and during the night (weighted volumes per street segment, median across runs); "+" indicates segments for which the volumes generated during the night are higher than the ones generated during the day; "-" indicates segments with lower volumes.

a thorough evaluation of the ABM macro-level patterns. For the sake of calibration and empirical parametrisation, the model would also benefit from the collection of explicit empirical evidence on route choice behaviour of vulnerable pedestrians at night; for example, GPS tracking devices could be used to acquire information about individual spatial choices taken by a diverse range of subjects. These steps are necessary to make any ABM a credible tool both for supporting the refinement of existing theories and informing policy-making. Finally, at the behavioural level, the ABM could be furthered by including adaptive learning over multiple journeys in the agent architecture, i.e., *spatial learning*, and by devising more complex social interactions between agents.

Although our results only partially emphasise the impact of nighttime on pedestrian movement, the model developed in this paper provides a novel approach to capturing temporal variations by integrating both environmental and psychological considerations into an agent-based simulation for pedestrian movement.

Declaration of Generative AI in writing

The authors declare that they have not used Generative AI tools in the preparation of this manuscript. All intellectual and creative work, including the analysis and interpretation of data, is original and has been conducted by the authors without AI assistance.

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