Towards a Validation Taxonomy for Agent-Based Models of Pedestrian Movement in Cities

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Abstract

Agent-Based Models (ABMs) are increasingly used to simulate and analyse pedestrian movement in cities and to support urban planning and policy decisions. However, their credibility depends critically on rigorous empirical validation, for which no standardised framework currently exists. This paper addresses this challenge by providing a structured synthesis of existing validation strategies, tailored to ABMs of pedestrian movement in cities, focusing on the comparison of simulated and reference behaviours. First, it reviews and systematises operational validation approaches spanning three model output levels: micro, meso, and macro. Then, it develops a validation taxonomy that links specific model outputs – individual behavioural trajectories, segment-level flows, and aggregate system indicators – to data sources, potential validation methods, and appropriate behavioural claims. Finally, it demonstrates the implementation of these approaches using illustrative examples. Here, it is argued that not only do different model outputs require distinct data sources and methodological strategies, but the generalisations a validation exercise can support are bounded by what is validated and how. The paper advances a practical validation taxonomy that, whilst setting standards in the discipline, can be flexibly adapted to diverse modelling contexts. In doing so, it supports the development of more robust, transparent, and policy-relevant agent-based models of pedestrian movement in cities.

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1 Introduction

Agent-based modelling is a computational paradigm that explores the behaviour of autonomous entities such as humans, social organisations, and animals in their environment. This framework is widely adopted to simulate, explore, and understand pedestrian dynamics in urban space. Agent-Based Models (ABMs) of pedestrian movement in cities have been developed at a variety of geographical scales, ranging from large urban areas to districts and neighbourhoods [4, 15]. Varying levels of behavioural complexity have been incorporated in pedestrian agents' route choice behaviour – that is, how agents formulate routes between different locations in the simulated environment – with many models resorting to shortest-path-based approaches.

Although recent modelling efforts have substantially increased the realism and sophistication of ABMs of pedestrian movement in cities, empirical validation has not progressed at the same pace [14, 13]. This gap matters: validation "relates to the extent that the model

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adequately represents the system being modelled" [3, p. 419], or, more operationally, whether "the model's accuracy is within its acceptable range of accuracy" [17, p. 12]. Several challenges contribute to this gap, including: i) limited availability of open, high-quality pedestrian data, and persistent privacy constraints [11]; ii) the cost and technical complexity involved in collecting and handling empirical validation data [7]; iii) the absence of universally accepted standards or one-size-fits-all approaches to validation in agent-based modelling [2]. Concerns about the reliability [4] of model outputs not only diminish the methodological relevance of the work, but also limit the ability of these models to shed light on principles of pedestrian movement and behaviour as a theoretical contribution, and advance policy-relevant insights or planning solutions.

ABMs of pedestrian movement in cities are used for different purposes: to explain and understand existing movement dynamics, test potential planning or design interventions, and estimate pedestrian movement under alternative system conditions. These purposes do not require the same form of validation. A model intended to reproduce aggregate pedestrian volumes, for instance, should not necessarily be evaluated in the same way as a model intended to represent individual route choice, behavioural adaptation, or localised responses to environmental conditions. Validation therefore needs to be aligned with the model output and with the claims being made.

This paper makes three contributions. First, it develops a structured taxonomy linking micro-, meso-, and macro-level model scopes and outputs to appropriate validation strategies. Second, it provides practical, step-by-step examples demonstrating how particular data sources can be leveraged for empirical validation through different operationalisation. Finally, it systematises existing validation strategies in the context of ABMs of pedestrian movement in cities and proposes a framework for linking model outputs, empirical data sources, validation strategies, and the behavioural claims they can support.

2 Operational validation in ABMs of pedestrian movement in cities

In this work, following [17], validation is approached as a problem of *operational validity*, that is, whether the output patterns of a simulation model have a satisfactory level of accuracy for the model's intended purpose and domain of applicability. The central argument is that different model outputs support different behavioural claims and therefore require different validation strategies. In ABMs of pedestrian movement in cities, the same model may generate several forms of output behaviour, including individual trajectories, route choices, walking times, segment-level pedestrian flows, spatial distributions of agents, temporal activity profiles, and system-level relationships.

In this direction, we distinguish between two operational validation procedures: exploring model behaviour and comparing output behaviours. On the one hand, *exploring model behaviour* refers to the systematic examination of the outputs produced by the ABM under different parameter values, behavioural assumptions, spatial representations, and experimental conditions. This may include sensitivity analysis, scenario inspection, and assessment of whether simulated patterns respond plausibly to changes in the model specification. This procedure is especially important when direct empirical observations are unavailable, incomplete, or not directly comparable with model outputs. On the other hand, *comparing output behaviours* refers to the direct assessment of simulated outputs against empirical observations, outputs from other models, or theoretical benchmarks. In observable systems, this comparison can be made against empirical pedestrian data, such as GPS traces, video-derived trajectories, pedestrian counts, aggregated mobile-device data, or platform-derived activity indicators.

This logic underpins the taxonomy used here. We focus on comparing output behaviours, organised across three output levels: micro-level validation concerns individual agent properties and emerging behaviours, targeting *behavioural consistency*; meso-level validation concerns collective movement flows across space and time, targeting *spatial and temporal consistency*; and macro-level validation concerns aggregated system-level patterns and model-wide distributions, targeting *aggregated logical consistency* or *theoretical plausibility*. These validation levels are analytically related but not interchangeable. Micro-level outputs may aggregate into meso-level flows, and meso-level patterns may contribute to macro-level system behaviour. However, each level captures a different abstraction of pedestrian movement and supports different claims. Validation should therefore emerge from the model purpose and output structure, rather than be carried out as a generic post-hoc exercise.

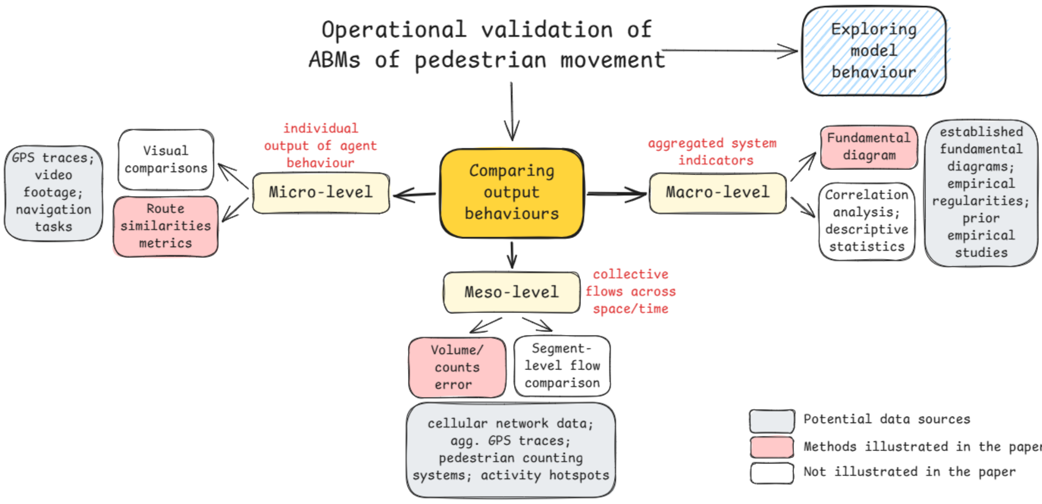

Figure 1 Approaches to *operational validation* of ABMs of pedestrian movement in cities.

2.1 Illustrative ABM case studies

To schematise potential validation strategies, we draw on two illustrative agent-based modelling case studies based on different modelling principles. The first ABM, hereafter referred to as *Case Study I*, simulates pedestrian movement in the Old Market Square in Poznań, Poland[1] [20]. In this model, agents enter and exit the simulated urban space through gateways linked to transport nodes. They then navigate towards randomly assigned Points of Interest (POIs) distributed across the square using a gradient-based movement mechanism, before returning to their entry gateway. As agents follow a gradient-based mechanism, this model is oriented towards explaining collective and system-level movement dynamics, and is used here for meso- and macro-level validation.

The second ABM, referred to as *Case Study II*, simulates pedestrian movement in the historical centre of Poznań. In this case, agents compute routes on a primal graph representation of the street network and travel from home locations to randomly selected POIs [21]. Here, as agents compute explicit routes, the model is oriented towards representing individual route choice, and is used for micro-level validation against observed trajectories.

[1] Poznań is a city located in west-central Poland, with a population of approximately 550,000 inhabitants; Old Market Square is the main square in the city centre.

2.2 Micro-level validation: Individual agent properties and emerging behaviours

Micro-level patterns refer to variables that capture individual behaviours. These include agent states (e.g. position, heading, speed, acceleration patterns, pedestrian interactions), as well as direct manifestations of behaviour, such as individual movement trajectories or distance travelled. Here, the validation exercise involves using high-resolution spatio-temporal data to verify the accuracy of simulated pedestrian behaviour against real-world movement. Research questions at this level of abstraction investigate, for example, the extent to which the agent routes match those observed in empirical data. In some cases, when the ABM explores more granular behaviour, these questions could even refer to locomotion details, avoidance behaviours, and so forth.

To illustrate this, we compared GPS traces recorded during a navigation task, in which 18 participants completed routes between fixed pairs of Origin and Destination (OD) points (36 routes in total) [22], with routes generated in *Case Study II* for the same OD pairs. Figure 2 displays both the agent routes generated by the ABM and the observed GPS traces.

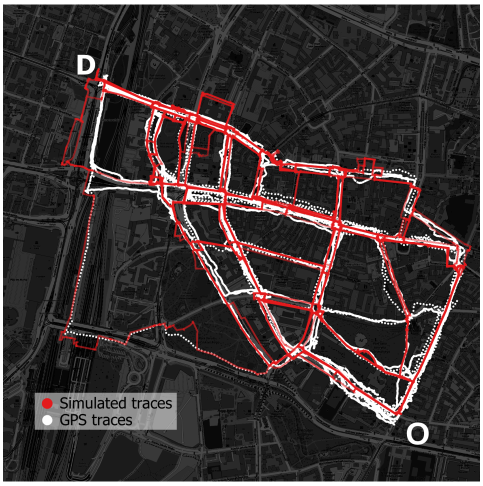

Figure 2 Simulated routes from *Case Study II* and the corresponding observed GPS traces.

While differences between individual trajectories and simulated outputs might be identified visually, several techniques can be used to quantify the divergence between simulated and observed routes, including Dynamic Time Warping, Fréchet distance, entropy-based measures, and directional change analysis [18]. In *Case Study II*, we adopted *point-to-point Euclidean error* as the accuracy metric. Specifically, the mean *route discrepancy* was computed as the average point-to-point distance per route, then averaged across the 36 routes, with smaller values indicating greater similarity between simulated agent behaviour and observed pedestrian movement. Furthermore, we compared measures of central tendency for route length and walking time across simulated outputs and empirical GPS data (Table 1).

Table 1 Properties of the simulated routes from *Case Study II* and the corresponding observed GPS traces (means across 36 routes from 18 participants).

Route Length (m) observed	Route Length (m) simulated	Route Discrepancy (m) mean / median	Walking Time (min.) observed	Walking Time (min.) simulated
2030	2014	5.2 / 3.52	20.04	20.58

This approach heavily depends on the availability of high-resolution trajectory data and is sensitive to sampling bias, positional error, map-matching choices, and the representativeness of the observed routes. Despite these challenges, micro-level validation remains one of the most behaviourally detailed approaches available for empirically validating ABMs of pedestrian movement. Crucially, accuracy at this level does not by itself support claims about collective flows or system-level dynamics.

2.3 Meso-level validation: Collective movement flows across space and time

Meso-level outputs refer to the spatial and temporal distribution of pedestrian agents. These outputs may include agent counts on street-network segments, pedestrian volumes at representative locations, such as city squares, green areas, or bus stops, or counts aggregated to spatial units such as census areas or hexagonal cells. When temporal dynamics are relevant, these counts can also be aggregated by time interval, for example to compare pedestrian activity across different times of day.

The most direct validation strategy at this level is to compare simulated outputs with observed pedestrian counts. Municipal pedestrian counting systems[2] provide one such source, as they rely on counting devices distributed across parts of the street network. These datasets can offer high temporal granularity, although their suitability for validation depends on the number and spatial coverage of the sensors. A second option is to make use of datasets that describe human activity hotspots [12, 9]. Such data indirectly capture how pedestrian presence varies across locations and time, and may be derived from aggregated GPS traces, cellular network records, or other crowdsourced signals. An example is Google's Popular Times service, which provides anonymised estimates of place-based busyness throughout the day and week. These datasets may represent pedestrian activity either as relative intensity indices or as counts associated with specific points of interest or street segments. They can be accessed through APIs or open data portals and may provide broad spatial and temporal coverage across urban environments. Images obtained from security cameras, video sensors, or scene-analysis methods can also be used to infer pedestrian presence and constitute an alternative source of meso-level validation data. Recent work, for example, has estimated street segment pedestrian volumes from Street View images of Tianjin (China) by leveraging machine-learning pedestrian detection techniques [1].

Validation research questions at this level may therefore investigate whether the model can reproduce observed spatial and temporal patterns of pedestrian presence across the simulated space. The geographical representation may be the street network itself, a set of relevant locations, or aggregated spatial units, at different scales of analysis. For illustrative purposes, Google Popular Times data for Old Market Square in Poznań were used to derive proportional activity levels around places and, therefore, as a proxy for pedestrian volumes during a Sunday. The upper panel of Fig. 3 presents the aggregated pedestrian volumes generated by *Case Study I* and compares them with pedestrian traffic derived from Google Popular Times[3]. The lower panel displays the error between simulated and empirical values.

The scaled series can then be compared using standard error metrics. In this illustrative case, the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were 29.86, 20.38, and 19.57, respectively.

[2] Sensor-based pedestrian count data are available for e.g. Melbourne (`https://www.pedestrian.melbourne.vic.gov.au/`), New York (`https://www.nyc.gov/html/dot/html/about/datafeeds.shtml`), or the City of Casey (`https://data.casey.vic.gov.au/`).

[3] Pedestrian numbers were scaled to a 0–1000 interval to make the two series comparable.

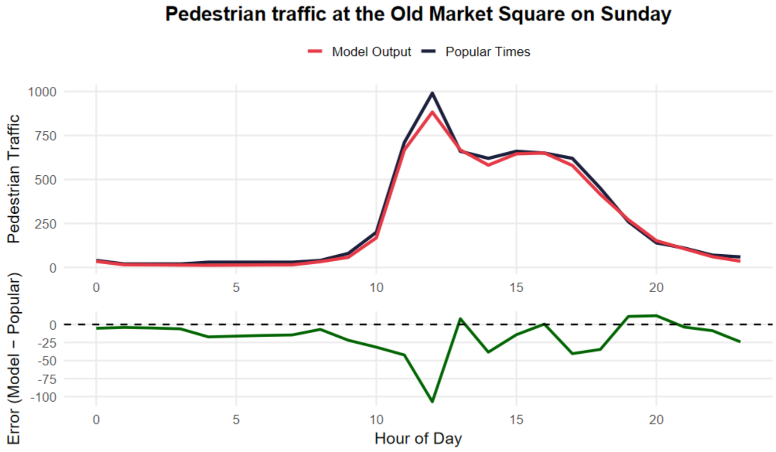

Figure 3 Popular Times-derived pedestrian activity data and the outputs of *Case Study I*.

Finally, existing work also highlights the potential value of adopting complementary techniques for validating meso-level outputs. Pouke and colleagues [16], for example, used mobility traces from a municipal Wi-Fi network to construct a time-varying OD matrix, which was then treated as a ground-truth representation of pedestrian movement across locations and time periods. Simulated pedestrian footprints were compared against this reference to identify where the model over- or under-estimated pedestrian presence at different times of day. Similarly, Filomena and Verstegen [5] evaluated simulated pedestrian volumes at the street segment level by deriving observed segment counts from a set of overlaid GPS trajectories. Their validation combined a spatial diagnosis of over- and underestimation across individual street segments with a network-level error assessment based on RMSE.

The scope of the claims that one can advance at this level is bounded: reproducing aggregate spatial and temporal patterns of presence supports deriving insights about collective pedestrian activity, but not about individual behavioural mechanisms generating those patterns.

2.4 Macro-level validation: System-level behavioural patterns

Macro-level and low-granularity aggregated outputs capture system-level characteristics, such as pedestrian flow rates, total volumes, average route length, density–speed relationships, and other aggregate regularities, and are commonly used to assess the overall logic of the simulated system. These outputs, rather than being validated directly in terms of fine-grained empirical accuracy, can be scrutinised to provide a general evaluation of the model.

Along these lines, for example, the *fundamental diagram* of pedestrian flows describes the relationship between pedestrian density, walking speed, and flow [19]. It typically shows that, as density increases, walking speed decreases, while flow – defined as *density* × *speed* – initially increases, reaches a maximum, and then declines under congested conditions [8]. In this context, the fundamental diagram serves as a theory-driven benchmark rather than a strictly location-specific empirical reference. The fundamental diagrams derived from the outputs of *Case Study I* are presented in Fig. 4, while the corresponding regression models are reported in Table 2

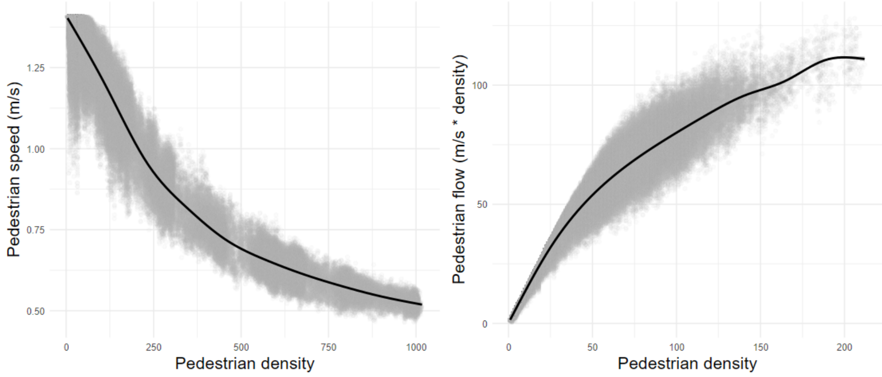

Figure 4 Fundamental diagrams of the simulated pedestrian flows in *Case Study I*.

Table 2 Coefficients of speed–density (regression model I) and flow–density (regression model II) relationships for the outputs of *Case Study I*.

Regression model	I	II
const	1.34^{***}	6.54^{***}
	(0.000)	(0.000)
speed	-1.10^{***}	–
	(0.000)	
flow	–	0.79^{***}
		(0.000)
R^2	0.92	0.93
F statistics p-value	0.000	0.000

Note: p-values are reported in brackets.

This sort of outputs can be examined using either location-specific data or studies that have estimated fundamental diagrams in different urban contexts. For example, empirical studies consistently confirm a negative relationship between pedestrian speed and density, with reported coefficients of determination (R^2) ranging from 0.78 to 0.99 [10]. However, estimated regression parameters vary across studies, with intercepts typically ranging from 1.0 to 2.0 and density coefficients from -0.7 to -1.3 [6].

Along similar lines, modellers have compared aggregated model outputs with empirical evidence reported in the literature with regards to, for instance, pedestrian preferences or behavioural characteristics. Although these assessments look at micro-level behaviour, they typically evaluate it through aggregated properties of agent routes, such as percentage deviation from the shortest path, and compare these outputs with empirical research on the determinants of route-choice behaviour. This type of assessment, when used to identify which ABM scenario or model configuration performs better against observational data, evaluates the behavioural plausibility of the model. One could argue that macro-level validation supports explanatory plausibility rather than direct predictive accuracy, as it assesses whether simulated outputs reproduce theoretically and empirically established patterns of pedestrian behaviour.

Unlike other approaches, this form of validation does not necessarily require external datasets specific to the case study. Instead, it relies on well-documented empirical regularities in pedestrian research. Nevertheless, several limitations should be noted. First, assessments based on the fundamental diagram refer to generalised empirical regularities rather than context-specific measurements. Second, pedestrian behaviour may deviate substantially from theoretically derived relationships because of individual heterogeneity and specific environmental or spatial configurations. Third, this type of validation does not directly evaluate route-choice behaviour, pedestrian spatial distribution, or temporal fluctuation patterns. As such, macro-level validation strategies, including those based on the fundamental diagram, should be understood as complementary rather than stand-alone validation approaches.

3 Synthesis: Towards a validation taxonomy

The examples above show that validating ABMs of pedestrian movement in cities is not a single methodological operation, but a structured process of aligning model scope, outputs, reference evidence, validation methods, and modelling claims. Table 3 presents a preliminary validation taxonomy that links levels of model output to corresponding data sources, methodological approaches, and the types of claims and insights the ABM can support. The taxonomy concerns the comparison of output behaviours, and it assumes that reference evidence is available; when direct comparison is not possible, the exploration of model behaviour (see above) remains the main alternative. The taxonomy is not intended to prescribe a universal metric or fixed validation threshold. Rather, it offers a reasoning structure for making validation choices explicit and comparable across ABMs of pedestrian movement.

Table 3 A preliminary validation taxonomy for pedestrian ABMs, linking output levels and model outputs to validation targets, potential data sources, methodological approaches, and the types of claims each can support.

Output level	Model outputs	Validation target	Reference evidence	Validation methods	Claims supported
Micro-level	Individual routes, trajectories, walking times, travelled distance	Behavioural consistency of individual agents	GPS traces, video tracking, lab-based navigation data, observed route choices, etc.	Route overlap, point-to-point error, Fréchet distance, Hausdorff distance, Dynamic Time Warping, entropy-based measures, directional change analysis, travel-time comparison, etc.	Claims about individual route choice, wayfinding, behavioural adaptation, decision rules, and agent-level movement realism
Meso-level	Segment-level flows, agent volumes, spatial concentrations of agents, temporal activity profiles	Spatial and temporal consistency of collective movement	Pedestrian counters, aggregated GPS traces, mobile-phone data, sensor networks, platform-derived activity indicators (e.g. Popular Times), image-derived counts, etc.	RMSE, MAE, MAPE, GEH statistic, temporal profile comparison, density surface comparison, segment-level flow comparison, hotspot comparison, spatial correlation analysis, etc.	Claims about collective pedestrian presence, public-space usage, temporal fluctuation, activity intensity, and local flow patterns
Macro-level	Aggregate system indicators, density–speed and density–flow relations, average route length, network-level measures	Aggregated logical consistency or theoretical plausibility of system dynamics	Published fundamental diagrams, established empirical regularities, outputs from other models, prior empirical studies, etc.	Distributional similarity, comparison of estimated coefficients with empirical ranges, comparison with theoretical expectations or benchmark simulation models, etc.	Claims about internal consistency, emergent patterns, theoretical plausibility, and congestion dynamics

The taxonomy addresses a common ambiguity in agent-based modelling for pedestrian movement simulation: treating visual plausibility, aggregate fit, behavioural realism, and theoretical consistency as equivalent forms of validation. From a spatial information perspective, the taxonomy highlights that validation is inseparable from spatial abstraction. ABMs of pedestrian movement in cities go beyond simulating pedestrian trajectories; they encode assumptions about space, scale, topology, accessibility, interaction, and decision-making. The output level at which a model is validated should also be aligned with its purpose: models used for prediction require stronger empirical comparison at the relevant output level, whereas models intended for explanation or scenario testing may resort to behavioural plausibility and system level consistency. This proposed taxonomy should therefore be understood as a flexible framework for designing and reporting validation exercises. At minimum, a validation claim should specify: i) which model output is being assessed; ii) which reference evidence is used; iii) which metric, diagnostic, or benchmark is applied; and iv) what claims the validation result supports. Making these elements explicit would improve transparency and reproducibility across agent-based modelling of pedestrian movement.

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