An Agent-Based Model of Public Space Use

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Abstract

Computational models have been described as exceptionally adept at examining the complex relationships of human and crowd behaviour, with a significant portion dedicated to investigating spatial behaviour in defined environments. Within this context, this paper presents an agent-based model (ABM) for simulating activity in public spaces at the level of the individual user. Although other ABMs of individuals' spatial activity exist, they are often found to simulate specific building-related activities, and fewer still are found to examine activity in public spaces, in a systematic manner. This research provides a generalized formalization of human spatial behaviour incorporating stationary activities and social interaction within a 3D environment, and is presented using a widely accepted framework for describing ABM, the Overview, Design Concepts, and Details (ODD) protocol. A sample study using a synthetic environment is used to demonstrate applicability, and the model is tested extensively to establish robustness. Furthermore, model output is compared to observed activity patterns in other studies of similar spaces, and simulated spatial patterns of activity are found to match those observed in real-world scenarios, providing insight into the dynamics of the processes, and highlighting the potential of this approach for studying the complexities of human spatial behaviour.

Keywords: Agent-based modelling, Public space, Computer simulation, 3D, ODD model description

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1. Introduction

Human spatial behaviour is a process the majority of people engage in automatically and often take for granted in their every day life, constantly taking into account stimuli from multiple sources and adjusting their behaviour accordingly, often subconsciously. Aspects that can affect one's behaviour in space may include their own needs and requirements, their current comfort, the existence and behaviours of others around them, and the opportunities and constraints presented by the layout of the physical environment around them, among others. As such, human spatial behaviour has been approached through multiple research disciplines, each examining a particular aspect and its effect on the resulting behaviour.

The inter-relationship between the physical environment and human spatial behaviour in particular is one of the foci (if not the main one) of architectural and urban design; In the design profession, practitioners shape physical environments (be it buildings or outdoor urban spaces) in such a way as to accommodate human spatial behaviour as best as possible with regard to the space's intended use. This process depends on designers' skill and expertise on translating form and physical layout into expected user activity and anticipating users' needs as best as possible, and often relies on existing knowledge of how people have used space in similar situations, extrapolating for the needs of the current design.

Such specific information about how people have used space is usually captured through a process called *'post occupancy evaluations'*, performed both for buildings (Hadjri & Crozier, 2009) as well as urban public spaces (Whyte, 1980; Gehl Architects, 2004). Post occupancy evaluations help designers understand how a space is actually used by its inhabitants/users, often by recording activity in a space through surveys in order to identify patterns and highlight any issues with the final produced design.

In addition to providing information on how a particular space is used, post occupancy evaluations can further offer some additional insights into the driving characteristics of human spatial behaviour, and help build an archive of knowledge on human spatial behaviour. More specifically, they can provide a better understanding on how people use space in general, both in regard to the physical environment, as well as the way people interact with one-another in space. For example, one such instance of human interaction in public spaces is the largely accepted axiom in urban design which broadly states that human activity at adequate capacity in a public space is in itself an attractor for other people to engage in activities in that same space. This has been observed and stated in multiple cases: Jacobs (1961, p. 45) writes: *"Large numbers of people entertain themselves, off and on, by watching street activity"*. Whyte (1980, p. 33) notes: *"All things being equal, ... where pedestrian flows bisect a sittable space, that is where people will most likely sit"*. Similarly and more succinctly, Gehl (1987, p. 25) observes that *"people come where people are"*.

However, one important point to highlight here is the fact that one of the most basic functions of any product of spatial design, its use by its occupants, is often not able to be fully investigated *during* the design process, but rather only *after* the design is finished and delivered to its users. Therefore, although observations on space use have built a significant archive of human spatial activity, this knowledge often remains largely empirical. Furthermore, the above mentioned observations on the attractiveness of crowds in public space highlight another important characteristic of human spatial co-interaction, the fact that human activity in space (and especially public spaces) demonstrates highly complex behaviours, often exhibiting non-linear relationships, with the behaviour of any one individual affecting and at the same time being affected by the behaviours of others in the space space. As such, both the process of capturing such information as well as the fact that observed behaviours demonstrate complex inter-relationships pose significant limitations for the systematic investigation of human spatial behaviour.

One approach that shows considerable promise in overcoming such limitations is computational simulations, as simulations can provide us with "artificial laboratories" to test ideas and hypotheses about phenomena which prove to be "wickedly" complex in the real world (Gilbert, 2007). A specific approach in computational simulations that is highly relevant here is agent-based models (ABMs), in which *"a system is modeled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules"* (Bonabeau, 2002), and could therefore be quite applicable in capturing the complex nature of human interaction in public spaces.

Therefore the development of an ABM that captures public space use may help provide a controlled environment to better understand human spatial activities as they take place in the real-world, by allowing us to explore the dynamics and processes that take place in interactions between individuals, as well as interactions between individuals and the environment. To this end, this paper presents the development and application of an ABM for simulating public space use at the level of the individual user. Existing computational approaches to spatial design and behaviour are discussed in section 2 with recent trends in computational simulation in architectural and urban design, and limitations of existing approaches are identified. The model is then described in detail using a widely used protocol for communicating ABMs in section 3, followed by a discussion on testing the robustness of the model as well as presenting the model's suitability for experimentation in section 4, along with an application of the model to a sample open urban space as a proof of concept, to demonstrate its relevance. Section 5 concludes with a discussion of the results and an outline of future work for the model.

2. Computational models of space use in architectural and urban design

This paper discusses a methodological approach to capturing and examining human spatial behaviour and space use as it takes place within well defined spatial environments. Hillier describes this concept of human spatial behaviour as the *generic function*, defining it as:

> *the spatial implications of the most fundamental aspects of human*

use of space, that is, the fact of occupation and the fact of movement. (Hillier, 2007)

It is important to clarify here that *space use* does not necessarily refer to a specific set of activities dictated by a building's or space's functional programme, but rather to the fundamental aspect of human spatial activity, that of *being in space*. Furthermore, when examining space use within the context of a well defined (i.e. designed) space, it is expected that the spatial configuration will have some effect on spatial activity. Therefore, if a study of space use is conducted within the scope of architectural or urban design, it follows that part of the study's focus is also placed on the effect a *design* decision might have on space *use*.

Space use in designed spaces is most often investigated after the design process has completed, through post-occupancy evaluations (Zimring & Reizenstein, 1980), which examine how a produced space is actually used. Such studies have been performed for buildings and indoor environments (Hadjri & Crozier, 2009), as well as outdoor spaces, such as urban public space (Whyte, 1980; Gehl, 1987; Gehl Architects, 2004). Such work is vital for building an archive of knowledge on human spatial behaviour, such that may be used in future design projects. Most often however results from post-occupancy evaluations may not directly apply to the design or building under investigation, as they take place after a project's completion and delivery to its users, at which point rarely any amendments to the design of the space under study can take place.

Post-occupancy evaluations have been the de facto method for examining the effect of spatial design on space use in the architectural field. However, pre-occupancy evaluations of space use that may influence design decisions may still take place, through the use of models. Models of spatial human-environment interaction can be formulated based on previous observations, and subsequently applied to a virtual representation of a proposed design. This application then allows for an examination of how future occupants may act within the space, and can help inform design decisions. Such models have become more and more relevant with the increase in computing power along with computer-aided design (CAD) and building information modelling (BIM) (Yan, 2008), allowing for more detailed scenarios to be examined during the design phase.

In the architectural design field and focussing specifically on the generic function, three main modelling approaches are identified here which aim to capture space use in relation to the design of space: *Space Syntax* methodologies, *pedestrian and crowd modelling*, and *spatial use behavioural models*. The three approaches discussed here are only identified in broad terms, as it is often the case that a particular model will include aspects from multiple categories, for example a space use model will most likely include pedestrian movement as one of its core functions, or a space syntax analysis may inform and drive a pedestrian model, as demonstrated for example by Penn & Turner (2001). Nevertheless, the core aspects of any model can often be traced to one of the three core categories discussed here, with each category demonstrating a set of unique principles, and so each will be presented independently to better illustrate recent advances in space use behavioural modelling studying human spatial behaviour as a result of spatial design.

2.1. Space Syntax methodologies

Space syntax is a set of analytical tools, which aims to capture social activity as it may be identified through spatial configuration (Bafna, 2003). Its driving principle is to capture space and spatial relationships, and furthermore to codify these relationships in a way that may allow for further analysis, in order to identify if and how they affect space use (Hillier, 2007). Its principal tool is the graph representation in which aspects of space are represented as nodes and their relationships as edges connecting individual nodes, with derivative tools including the *convex map*, the *axial map*, and the *visibility graph*, all methodologies for capturing an aspect of space. Social activity (and subsequently user spatial interaction) is then calculated as a function of spatial characteristics. At its core, space syntax therefore presents a deterministic model of space use.

Space syntax has seen significant application in the architectural profession.

Examples for indoor space syntax analysis include workspace analysis using visibility graphs (Sailer & McCulloh, 2012; Sailer et al., 2016), in which social ties and inter-personal interaction between colleagues (and thus very relevant space use) is examined as a result of spatial configuration (Koutsolampros et al., 2018). In a similar fashion, outdoor urban activity in terms of route preference has been studied extensively using graph networks and axial maps (Penn, 2003; Turner, 2007), demonstrating its applicability across multiple scales of the architectural and urban design professions (Dursun, 2007; Karimi, 2012).

2.2. Pedestrian and crowd modelling

Pedestrian and crowd models encapsulate a wide range of modelling methodologies which attempt to capture and reproduce the dynamics of people moving in crowds, most often through the application of path-finding and movement behavioural rules applied to the individual members of the crowd. Prime examples of this modelling approach are seen in evacuation and egress simulations in flow-critical environments, for example train stations (Castle et al., 2011). Such models have been applied to a variety of environment types, from restricted spaces in indoor environments (Pelechano et al., 2007), to open space in large outdoor environments (Batty et al., 2003; Torrens, 2015). A common feature in pedestrian crowd simulations is the focus on emergent crowd behaviour as driven by individual member behaviour at the local scale. At their core, such approaches often implement a stochastic model of space use, as individual entities are programmed to react to conditions in their local surroundings, including conditions as created by other entities acting in a similar manner.

Recent reviews of the wider field have been published elsewhere, demonstrating the extensive work of the field: Pelechano et al. (2008) discuss crowd simulations from a computer science and software design perspective, Papadimitriou et al. (2009) review transport-oriented pedestrian behaviour models, and Torrens (2016) presents a recent overview of the general field of crowd simulation covering *computational streetscapes* from multiple perspectives. There are some examples in this category that are not concerned with interaction between spatial design and use, specifically those that investigate fundamental aspects of crowd movement, for example the *social force model* by Helbing & Molnár (1995) formulating a model for people negotiating their movement in dense crowds. However the vast majority of the studies in this category apply these modelling methodologies on virtual crowds in defined spatial environments, either real or synthetic, in order to examine the effect spatial configuration has on the behaviour of crowds formed by autonomous individuals.

2.3. Spatial use behavioural models

Spatial use behavioural models include some very recent approaches to simulating individual users' activity in space. On the surface they implement similar approaches to pedestrian and crowd models in that their goal is to simulate aggregate space use, examined at the level of the individual. However, they differ from pedestrian and crowd models in one critical point (at least in the context of this paper), in that they purposefully include stationary and occupation activities, in other words spatial use models aiming to fully capture Hillier's *'generic function'*, as discussed previously. Earliest examples of such computational models of space use are identified in the work of Yan & colleagues (Yan & Kalay, 2004, 2005; Yan & Forsyth, 2005), whose proposed models aimed to simulate the spatial behaviour of users in a plaza as a function of the conditions of the built environment.

Subsequent work on the subject has expanded into the study of indoor and workspace activity (Schaumann et al., 2016), using preset *events* to drive simulated use (Simeone & Kalay, 2012; Schaumann et al., 2015), using hierarchical systems to dynamically satisfy constraints at multiple scales (e.g. at the building, room, and agent level)(Zhang et al., 2019), using computer simulations in academic architectural design courses (Hong et al., 2016), and overall actively focussing on early-stage design (Wurzer et al., 2012) and not-yet built environments (Schaumann et al., 2015). Although promising, this particular field is still quite new, and therefore not much work has taken place yet. Even so, some early trends can be identified: First, there appears to be a turn towards individual and agent-based models (ABMs) for the simulation of space use, and second, studies seem to be increasingly implementing three-dimensional space, both for visualisation as well as for computational purposes.

2.4. Limitations of existing approaches in simulating open public space activity

Having discussed existing approaches for modelling space use, it is also necessary to identify key aspects of the field of interest, i.e. actual human spatial behaviour in open spaces, in order to highlight the requirements that any model of such activity would need to take into account. Recording activity in real-world spaces is often performed using '*behavioural mapping, a technique used in environmental psychology and related fields for recording people's behaviors and movements systematically as these behaviors occur in particular locations*' (Ng, 2016). This technique is based on direct observation of people in a space, and requires the precise and narrow definition of all the different behavioural categories relevant to the area under investigation (Ittelson, 1970, in Ng (2016)), therefore the identification of relevant behaviours and activities is quite site-specific. Furthermore, depending on the area under investigation, it is possible for the number of activities to be quite large, as for example in Goličnik (2005), who in their work of recording behaviours in open spaces in two European cities defined 42 categories (Goličnik, 2005, Appendix B.1, p. 177).

In addition to the number of activities, the occurrence of each activity seems to vary by site as well. In a comparison of recorded stationary and movement activities (as shown in Table 1) between five urban parks in different European countries reported by two studies (Goličnik & Ward Thompson, 2010; Cheliotis, 2019)[1], the ratios between stationary and movement activities were found to differ significantly. Although expected, as different areas and cities could attract different activities, this nevertheless highlights the complexity of such spaces in their use profile.

[1] Activity counts for Edinburgh and Ljubljana were aggregated to more basic types by translating as was seen appropriate

Location		Total count	Movement activities		Stationary activities	
City	**Park**		**Count**	**%**	**Count**	**%**
Edinburgh	Princes Street Gardens	3254	1183	36.36%	2071	63.64%
	The Meadows Park	2768	1773	64.05%	995	35.95%
Ljubljana	Tivoli Park	3610	1876	51.97%	1734	48.03%
London	Hyde Park	4599	2142	46.57%	2457	53.43%
	Queen Elizabeth Olympic Park	2479	1127	45.46%	1352	54.54%

Table 1: Movement and stationary activities as a percentage of total recorded activity in 5 urban parks

Such variety in activities and probability of occurrence would be highly complex to simulate using one of the existing approaches. More specifically, Space Syntax methodologies present a deterministic model of spatial activity, and moreover spatial behaviour is modelled as a direct result of spatial morphology, rather than inter-personal interaction. Spatial use behavioural models present a fitting approach in terms of scale and scope, however models reviewed in this work were found to focus on more restricted environments, such as workspaces where activities were few and modelled explicitly. This poses a significant limitation, as it would be inefficient to codify for example all 42 activity types proposed by Goličnik (2005). Finally, pedestrian and crowd simulations, while they often propose a more fundamental mechanic for driving individual behaviour (e.g. as per the *social force model* by Helbing & Molnár (1995)), which could capture the variety of activities in more abstract form, focus mainly on crowd flows and movement activities, often excluding stationary behaviours.

Therefore, this paper identifies a need for a stochastic model of public space use that captures aggregate spatial activity as it emerges through the interactions of individuals operating on generalized rules of spatial behaviour. Furthermore, in order to capture the wide range of activities and their probability of occurrence as observed in real-world spaces, a more abstract representation of such activities is needed, such that specific activities can be mapped/translated to their more fundamental representation. As such, this paper proposes a model of public space use building on principles akin to Hillier's '*generic function*' (i.e.

using a broad classification of movement and stationary activities), and furthermore driven by more fundamental social proximity observations as stipulated by Whyte (1980) and Gehl (1987) and other observations recorded through behavioural maps.

3. An agent-based model of public space use

Given the particularities of the field under investigation, of spatial behaviour in open spaces as driven by the interactions of individuals within them, the model of pubic space use in this work is developed using the agent-based modelling (ABM) paradigm, as it has been argued that ABMs are quite adept at simulating spatial processes at the micro-scale (Heppenstall et al., 2016). More specifically, this work presents a model of park activity, with park visitors modelled as autonomous agents functioning on simple behavioural rules, who move and engage in activities based on a stochastic process. As was discussed in the previous section, the model of human activity requires a more abstract representation so as to include multiple activity types in their generalized form, as well as a wide range of different activity occurrences. As such, the base activity decision making process contains two fundamental activity types (Movement and Stationary) with agents changing between the activities based on variable activity probabilities, able to capture multiple different area use profiles. The term *'stationary activity'* is used here as an umbrella term for any type of activity that requires an individual to remain at a (relatively) fixed location for the duration of it. This representation provides a functional framework for simulating behaviours where the exact process may not be known, and additionally provides the necessary flexibility to expand and include additional activities as needed, by adding new activities and probabilities to engage in.

Furthermore, given the scale of observation of the field of interest, that being the field of architectural and urban design, interactions between individuals exist wholly in and are influenced by the three-dimensionality of the environment. More specifically, multiple cases exist in which interactions observed in the real world may only be simulated in a 3D environment, as any reduction in spatial dimensionality would significantly alter the interaction (Cheliotis, 2019, p. 143), including for example visibility between individuals over different levels (e.g. as in a balcony over plaza scenario), movement over multiple levels with overlapping geometry (e.g. an overpass over a footpath), or the slope of the terrain affecting activities (e.g. in areas with significant landscape). As such, the ABM of public space use in this paper will be developed in a 3D environment.

The rest of this paper presents an ABM that captures public space use and human socio-spatial activity. The model presented here is still at an early stage of development, and aims to present a generalized formalization of human activity in public spaces. For this reason, it aims to capture public space use in broad strokes rather than present more specialized cases, and therefore a conscious effort has been made to simplify model elements where possible. Overall, the model incorporates observations and findings from public space use surveys mentioned previously and implements them in a sample park environment, as this type of location presents a fairly unrestrictive environment to test whether a model incorporating simple behavioural rules can generate use patterns observed in real world conditions. Furthermore, the model presented here was developed using the Unity engine (Unity Technologies, 2018), a 3D video game development and simulation platform (Juliani et al., 2018). Finally, ABMs have been introduced fairly recently in the architectural design field, and as such have not been documented and presented in a consistent method, a phenomenon documented by Angus & Hassani-Mahmooei (2015) when ABM are introduced in a new field. As such, this paper will implement the ODD protocol (Grimm et al., 2006, 2010) to describe the ABM of public space use, a standardized format for presenting ABMs, similar to how related fields have approached the presentation of models of pedestrian crowds (Crooks et al., 2015).

3.1. Purpose

The purpose of this ABM is to study the interaction between designed spatial environments on the one hand and human spatial behaviour in open public spaces on the other, by examining the extent to which simple behavioural rules at the individual scale (as hypothesized through empirical studies) can reproduce observed aggregate activity in public spaces.

3.2. Entities, state variables, and scales

There are three main entities in the model: The *agents*, the *environment*, and the *controller*. The *agents* are the dynamic entities in the model, the *environment* is the static physical environment within which the agents act, and the *controller* is a top level module that regulates the agent population and model scheduling processes.

3.2.1. Environment

The environment is a virtual represenation of a public open space[2] with significant landscape and overlapping geometry. Space is represented continuously, modelled using 3D mesh geometry at a reduced level of detail (i.e. using block geometry) rather than using high fidelity models and textures, to optimize rendering and computation in 3D space. One spatial unit in model space corresponds to one metre. Time is modelled as discrete time-steps, with each simulation tick representing one second.

The physical environment is further divided into distinct objects as needed. In this model, the terrain is divided into four distinct types: grass, paths, water, and roads, as this classification was considered to be a good balance between minimizing number of different terrain types, while allowing for adequate variation. Each terrain type exhibits different characteristics: *Paths* are the preferred walkable areas, and do not allow for stationary activities to be developed on them. *Grass* areas are navigable areas (with smaller weight compared to paths) that can host stationary activities. *Roads* are navigable areas (at smaller weights compared to grass areas) that do not allow for stationary activities. They represent vehicle space, and so in the context of a model of public

[2]For the purposes of presenting this model overview, a sample park environment was created

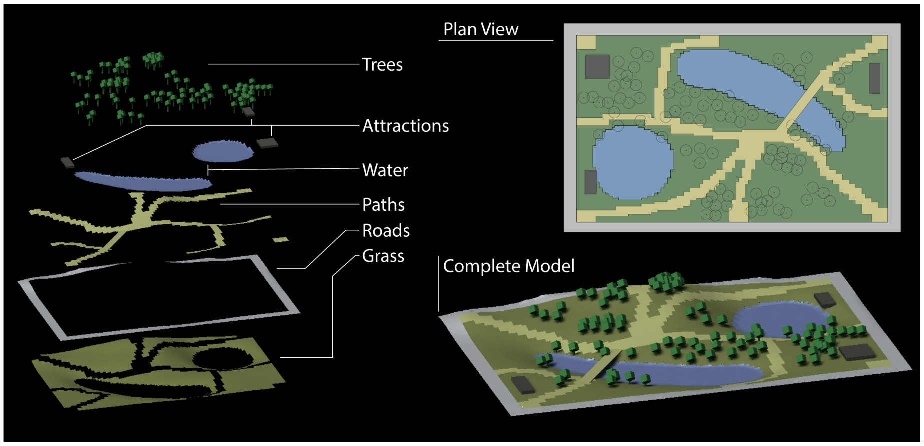


Figure 1: Virtual environment (right) with individual layers and features (left)

space use provide no utility other than necessary traversal space, and are used in this model to border the environment. *Water* surfaces are non-navigable areas (and therefore do not allow for any activities to be developed on them), and are essentially obstacles in almost every sense, with the notable distinction that they allow visual communication over them.

Further park features are added to the environment as individual objects, constrained to trees, attractions, and park gates in this model. Trees (representing both actual trees as well as bushes and shrubbery) present physical and visual obstacles, but do not present an obstacle regarding navigation. Attractions represent locations in the area of interest that contain features and other defined elements that might serve as a point of attraction (e.g. restaurants, amenities, monuments, etc.), and pose a physical obstacle regarding some activities. Gates signify the area entrances and exits, and in this model are placed at the area corners and mid-points of sides. Gates do not have a physical presence in the environment. The final 3D model of the environment along with a detailed view of individual layers and features is shown in Figure 1. The dimensions of the park model used for this paper are 500 by 300 meters.

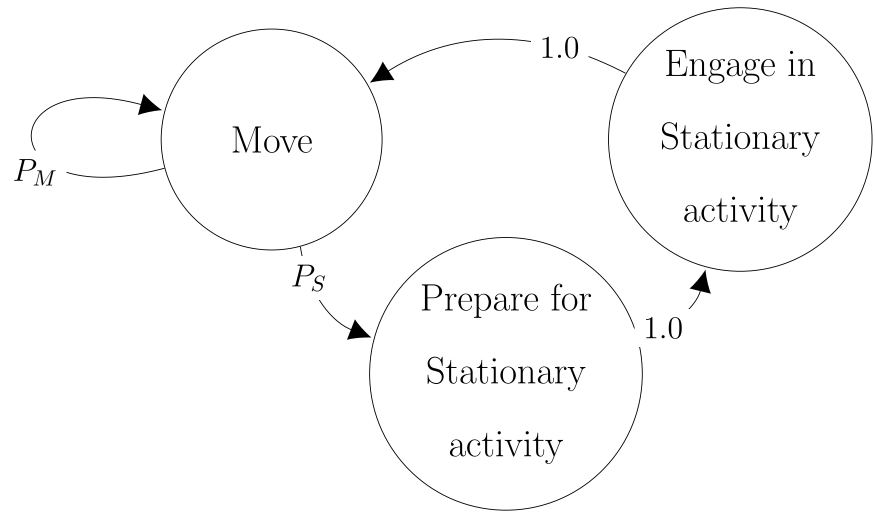


Figure 2: Abstract representation of the agent decision making process, modelled as a three state Markov chain

3.2.2. Agents

Agents represent human park visitors, with each agent representing a single individual visiting the area of interest for a predetermined duration. Agents have a physical presence in the model, represented using a simplified box geometry with dimensions 1/0.5/2 meters (width/depth/height), and have limited knowledge of the environment for the purposes of wayfinding and navigation, but otherwise rely on synthetic vision to detect other entities and features.

The agent decision making process is modelled as a Markov chain (Figure 2) with two core activity types (Movement and Stationary), each with probability values (P_M, P_S respectively) set by the user. Furthermore, stationary activities are assumed to potentially have some requirements for their deployment, whether they may be physical, such as an activity that takes place at a particular location (e.g. a cafe) or within a particular morphology (e.g. on flat or sloped terrain), or social, such as social interaction activities. As such, stationary activities furthermore may include a preparatory process which allows an agent to scan their environment and look for the optimal location, before engaging in the stationary activity for a specified duration.

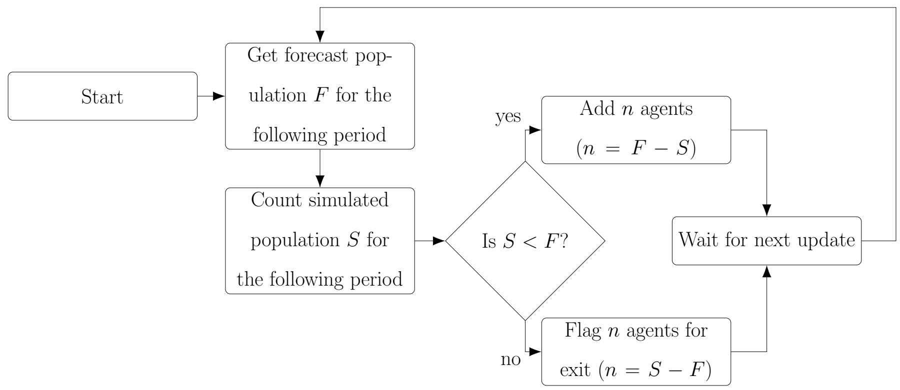


Figure 3: Controller logic

Agents are introduced into the simulation by the controller, and are removed in one of two ways, either through their own when their visit duration comes to an end, or prematurely via the controller, in cases where the simulated agent population surpasses the expected agent population.

3.3. Process overview and scheduling

The controller handles top level scheduling tasks including logging and monitoring, and controls the agent population numbers in the model. It updates at fixed intervals of 900 timesteps. At every update it determines the total agent population over the coming 900 timesteps, compares it to the existing and expected agent population, and adds new agents or flags existing agents to exit, as necessary. The controller is set up in this way to enable modulation of the agent population (e.g. to simulate daily activity cycles) without imposing significant control over individual agents' behaviours, thereby allowing external models to drive the agent population size at any point in the simulation. The controller logic is shown in Figure 3.

Agents are introduced into the environment at predetermined locations placed at the park entrances, marked as gates. Once an agent has initialized, it wanders in the area, keeping track of its time in the simulation (its age), and engages in stationary activities until its age reaches the predetermined visit duration (the agent's lifetime), at the end of which it moves to one of the park exits and

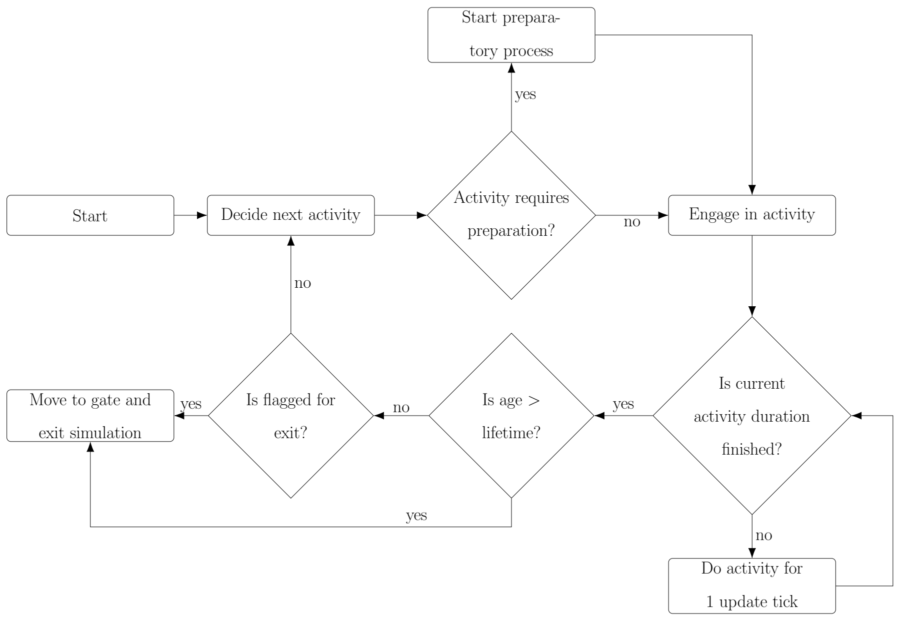


Figure 4: Agent behaviour flowchart

is removed from the simulation. During its lifetime, it operates based on the flowchart shown in Figure 4. Agents update during each step asynchronously, in fixed order, sorted by time of introduction (earlier agents act first).

3.4. Design concepts

3.4.1. Basic principles

The driving concept behind the ABM presented here is the often observed characteristic of crowd behaviour in public spaces mentioned previously, which broadly states that human activity at adequate capacity in a public space is in itself an attractor for other people to engage in activities in that same space, in addition to physical characteristics of space. Agents in the model are programmed to act in this manner, by engaging in stationary activities in locations chosen due to their social and physical conditions. In addition to the stationary activities, agents are allowed to move within the environment, providing an abstract framework within which agents as a whole move and respond to that movement by engaging in stationary activities.

3.4.2. Emergence

It is expected that agents operating on stochastic behavioural rules following the basic principles stated above, combined with the capacity to scan and survey their local surroundings, and placed in a well-defined (i.e. designed) environment, will collectively exhibit non-random spatial distributions of activity, with identifiable patterns directly relatable to the environment's layout and comparable to spatial behavioural patterns observed in real-world parks.

3.4.3. Objectives

Some agent stationary activities require a preparatory process, during which an agent will search for the optimal location to engage in the intended activity. Each such activity has a set of predefined spatial and/or social requirements, according to which the agent scores potential locations for the intended activity.

3.4.4. Sensing

Agents have a form of synthetic vision implemented in the model using raycasting, which they use to detect their local environment including obstacles, terrain types, and other agents.

3.4.5. Stochasticity

Model elements relating to agent behaviour and parameters are driven by stochastic processes, generating a heterogeneous agent set. More specifically, agent movement speed is drawn from a distribution, and agent lifetime is drawn from a distribution with a minimum threshold ensuring that even agents with short lifespans get to loop through their behaviour tree a few times. During an agent's activity decision-making process, the next activity that an agent will engage in as defined by the Markov process is selected using probabilities as set by the controller. Position sampling is performed by randomly selecting points on the ground around the agent's current location using a bivariate (2-dimensional) semi-circular distribution.

3.5. Initialization

At model initialization, the following elements are set: The state of environmental objects is set, for example the existence and location of area gates and features/attractions. Additionally, global values for agent behaviours are set, i.e. the parameters that are homogeneous across the agent population at the current time in the model development. These include the probabilities for each agent activity type, and agent sensory and interaction distances. At $t = 0$ agent population is 0; the model initializes with a controller update which sets the target population size, and agents are gradually introduced over many timesteps, to allow for dispersion within the area.

3.6. Input data

The model is able to utilize input data from external models to drive agent total population during controller updates, but can also function without using input data to represent time-varying processes. For the purposes of presenting the model in this paper no input data was used, but rather all values and parameters were set by the user.

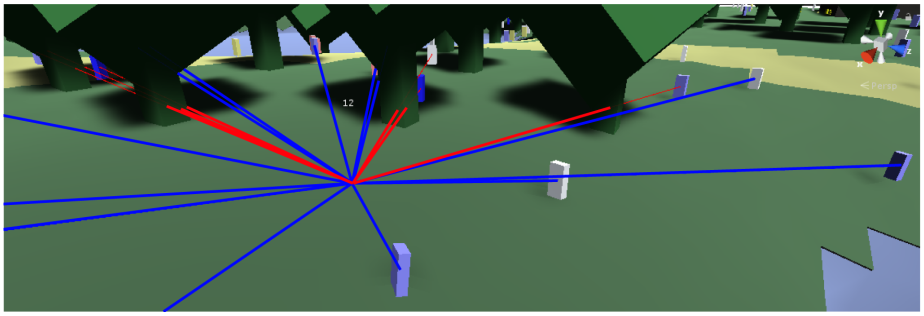
3.7. Submodels

3.7.1. Agent vision

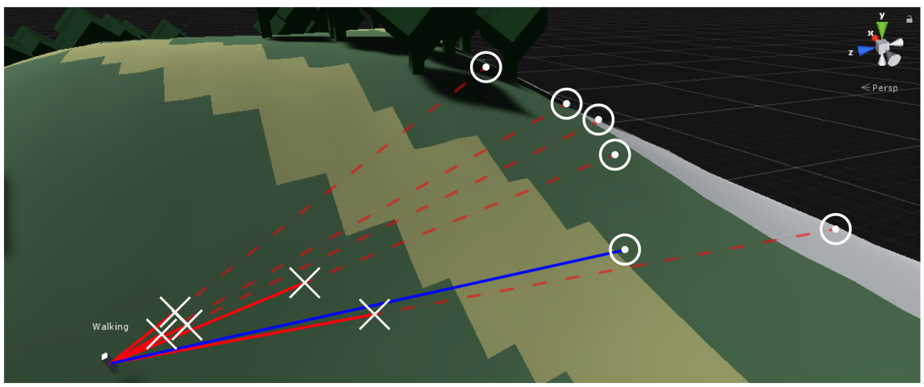
Agents employ a form of vision by using raycasting and similar physics-based collision detection. This form of synthetic vision is used to check what entities are visible from a particular location as shown in Fig. 5a, as well as during movement to identify potential move destinations (Fig. 5b), further illustrating the need for 3D environments in public space use models.

3.7.2. Move Activity

Agents use the A* pathfinding algorithm for calculating shortest paths on a navigation mesh to move in the environment. Two different implementations of path-planning are used: if an agent has a defined target location, regardless of distance (for example an exit gate), they will calculate the shortest path on the



(a) Raycasting vision to sample a location: other agents visible from a particular location (blue lines), and agents obstructed from view from that location (red lines)



(b) Raycasting vision to find valid move destination: For sampled locations (white circles), points without direct line of sight (red lines) due to sloped terrain are discarded

Figure 5: Agent vision

navigation mesh and on subsequent timesteps move at their speed towards it. If an agent is in a *Move* state, they move using an *angular-constrained random walk (ACRW)*: In ACRW, an agent will pick a new location at random within its current field of view (Figure 6), so that it has line of sight to it, the location is on valid terrain, and a valid path to it exists. Once such location is found, the agent calculates the shortest path to it on the navigation mesh, and on the following timesteps moves at its speed on the path until it reaches its target.

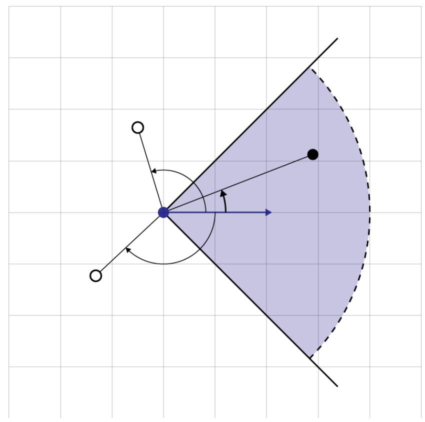


Figure 6: Agent field of view and random walk location decision process: The white points are discarded as potential target locations, as they fall outside the agent's field of view. The black point is chosen as a valid target location.

3.7.3. Stationary Activities

As discussed earlier (section 3), *'Stationary activity'* is a broad definition that encompasses all potential activities taking place at any fixed location, and may be expected to have additional requirements for their deployment. The general implementation of a stationary activity is straightforward, with agents currently engaged in a stationary activity essentially planting themselves at a location in the area and remaining there for the duration of the activity. However the actual stationary activity is preceded by a preparatory process, during which the agent scans its environment and samples locations using its vision capabilities to identify features, other entities, and terrain characteristics. Sampled locations are then scored according to the particular physical and social requirements of the stationary activity in order to identify the optimal location, and once such a location has been identified, the agent then proceeds to engage in the activity as discussed.

In order to apply the model to a scenario, stationary activities along with their requirements were defined, relevant to the area of interest. For brevity, and given that this is a preliminary study, three generic activity types were implemented that capture the full spectrum between physical and social conditions, on the assumption that any stationary activity may be described via a combination of requirements of the two extremes: A *Social* activity that only takes into account other agents, an *Environmental* activity that is tied directly to environmental conditions and the spatial layout, and a *Socio-Environmental* activity that relies both on environmental and crowd conditions.

The three activities described here translate broadly to three activity types often observed in parks: Visiting particular features and attractions (*Environmental* activity, in which a visitor moves directly to the point of interest), engaging in sports activities (*Socio-environmental* activity, which takes place in an area free of obstacles (e.g. no trees, water), and clear of other park visitors), and general leisure park visits (*Social* activity, affected by the existence of other park visitors according to observations on social proximity). This classification further appears adequate in capturing multiple detailed activities under a broader description, as is shown in Table 2, where the 42 activity types proposed by Goličnik & Ward Thompson (2010) are mapped to the abstract categories discussed here including the 'movement' activity.

Social activity. The *Social* activity is driven by the conditions presented by other agents in the model and is preceded by a pre-calculation phase. During the pre-calculation phase, a sampling loop takes place for a predetermined duration, during which *Move* activities are continuously implemented. While moving during pre-calculation, the agent samples nearby locations and scores them based on the number of other agents visible from that location. Each sampled location's score is the sum of all other agents within vision distance with direct line-of-sight, with a heavy penalty applied for each agent within very close proximity (termed the agent's *personal distance*) of the sampled location[3]. After sampling is finished, the agent moves to the location with the highest score, and remains there stationary for the activity duration. The sampling and

[3]This penalty is used so as to simulate the observation of personal space in interpersonal physical interactions.

Base category	Detailed description	Base category	Detailed description
M	Walking	M	Roller-skating
M	Cycling	M	Skateboarding
S	Standing	S	Sitting while roller-skating
S	Sitting	S	Sitting while skateboarding
SE	Sitting on a bench	S	Standing while skateboarding
SE	Sitting around a table	SE	Bmx acrobatics
M	Pushing a pram	S	Lying down
M	Walking a child	SE	Lying down on a bench
M	Walking a dog	SE	Sitting on a tree
M	Pushing a pram and walking a child	SE	Playing
S	Sitting with a pram	SE	Playing football
SE	Sitting with a pram on a bench	SE	Playing badminton
S	Sitting with a dog	SE	Playing frizbee
SE	Sitting on a bench while walking a dog	SE	Playing with a ball
S	Standing with a pram	E	Climbing
S	Stopping	SE	Rolling down
S	Stopping with a pram	SE	Flying a kite
S	Stopping with a dog	E	Fishing
S	Stopping – talking	M	Using a wheel-chair
M	Jogging	M	Pair situations: walking together
M	Propelling scooter	S	Pair situation: sitting together

Table 2: Mapping of detailed stationary activity descriptions, as proposed by Goličnik & Ward Thompson (2010), to base category

calculation process is shown in Figure 7.

Environmental activity. The *Environmental* activity is driven exclusively by conditions presented by the physical environment. It does not require a pre-calculation phase. At the start of an *Environmental* activity, an agent chooses one out of a set of predetermined attractions in the area at random, picks a location at random within close distance of the attraction (within 25 meters, simulating dispersion around the point of interest), and starts moving there. Once it reaches the target, it remains there stationary for the activity duration.

Socio-Environmental activity. The *Socio-Environmental* activity is driven by conditions presented both by the physical environment and by other agents and requires a pre-calculation phase. During the pre-calculation phase, a sampling

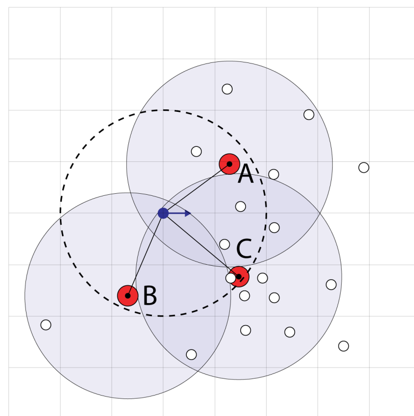


Figure 7: Social activity sampling process. For sampled locations A, B, and C and scores measured as +1 for each agent in view distance and −100 penalty for each agent within personal distance: A has a score of 7, B has a score of 2, and C has a score of -89 (+11 visible agents -100 for one other agent within personal distance)

loop takes place until an adequate location is found, during which *Move* activities are continuously implemented. While moving, the agent samples nearby locations for areas of a fixed radius that are free of obstacles and are on relatively flat terrain. Objects that are recognized as obstacles include: *Paths* and *Water* terrain, trees, buildings, and *more than one other agent not in Move or Socio-Environmental state*. Once a location is found, the agent moves to the location, and remains there stationary for the activity duration. While in a *Socio-Environmental* state, the agent is assumed to occupy the whole area within the fixed radius around the detected location. The calculation process is shown in Figure 8.

3.7.4. Agent decision-making process

An agent may therefore be engaged in one of four main activity types at any point in the simulation: *Move (M)*, *Social (S)*, *Environmental (E)*, and *Socio-environmental (SE)*. During each decision-making step, the decision for which activity to engage in next is performed using a stochastic process. With the addition of a pre-calculation step required for some of the stationary activities,

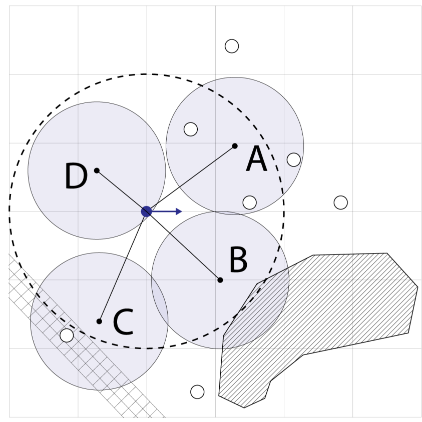


Figure 8: Socio-Environmental activity sampling process. For sampled locations A, B, C, and D: A is discarded for having 3 other agents, B is discarded for overlapping water geometry, C is discarded for overlapping with path geometry (one other agent is acceptable), D is valid.

the full decision-making process of the functional activities is shown here as a conditional Markov Chain (Figure 9), with the *Move* activity as the starting and default activity for agents. Probabilities for each of the activities were set by the modeller for each simulation run, as the model has not been calibrated to real-world data at this point.

3.7.5. Agent activity duration

Agent activity durations are divided into two categories, movement activity durations D_M and stationary activity durations D_S, which are handled differently. Movement activity duration is determined by the current path length and the agent's movement speed, with the agent keeping track of the average move activity duration over its lifetime.

Regarding stationary activity durations, it has been established (subsection 2.4) that public space user activities cover a wide range in terms of occurrences; furthermore, the occurrence of different activities is expected to be directly affected both by the duration of such activities, and by the activity probability, as longer and/or more frequent activities will have a higher chance of being observed. Additionally, activity durations are not known, activity oc-

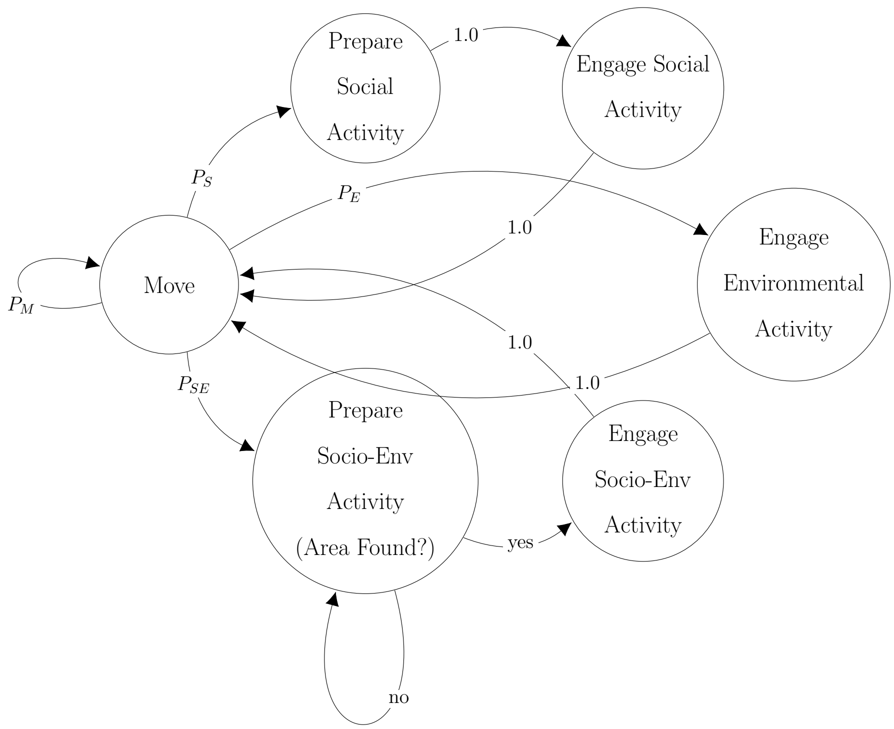


Figure 9: Agent activity decision-making process presented as a Markov Chain

currences (and therefore their probabilities) are shown to vary depending on case study, and finally activity probability may be set by the modeller depending on the area of interest. As such stationary activity durations D_S are calculated so that consistency is maintained between three parameters during the course of the simulation: for a given value x of the stationary activity probability, on average at any time in the simulation x percentage of agents should be engaged in that stationary activity, and furthermore agents should (on average) spend x percentage of their lifetime in that particular activity.

In order to maintain this consistency, the formula used to calculate the duration of a stationary activity D_S is dependent first and foremost on the duration of an average *Move* activity D_M, rather than assign a fixed value. This is done in order to provide a scaleable method, so that the ratio between move and stationary activities may be maintained in different scenarios where *Move* activities have different durations to the ones set in this model. Furthermore, in an ideal setup, D_S would be set to equal D_M and duration ratios between *Stationary* and *Move* activities would hypothetically be in agreement with the probability of engaging in a *Stationary* activity P_S as required, due to the Markov Chain setup[4]. However agent behaviour elements skew this ratio in favour of *Move* activities, specifically the *precalculation* stage for stationary activities (which is measured as time spent in movement) and the *Exit* process (which may lock an agent in a lengthy *Move* activity depending on the exit point chosen), and therefore D_S needs to be longer than D_M, to compensate. Furthermore, as higher probabilities for stationary activities introduce additional precalculation phases, stationary activity error increases for higher P_S, and as such the formula for calculating D_S needs to take into account P_S as well to allocate proportionally more time to stationary activities for higher P_S values. A comparison of different formulas is shown in Figure 10, to better illustrate the discrepancies discussed here. In order to maintain the consistency between stationary activity probability, agent engagement, and agent lifetime spent on activity, as discussed earlier, the final formula for D_S takes into account the average activity duration D_M, the average precalculation phase duration D_P, and the stationary activity probability P_S, and is defined as:

$$D_S = D_M * a + D_P * P_S^b * c$$

With variables a, b, c used for calibration. Trough trial-and-error, the values for a, b, c were set to $1.6, 2.0, 6.0$ respectively, which produced the best fitting curve.

[4]e.g. for $P_S = 0.1$, an agent would choose to engage in a stationary activity one out of ten times, and due to equal activity durations would therefore spend 10% of their time in stationary activity, as expected

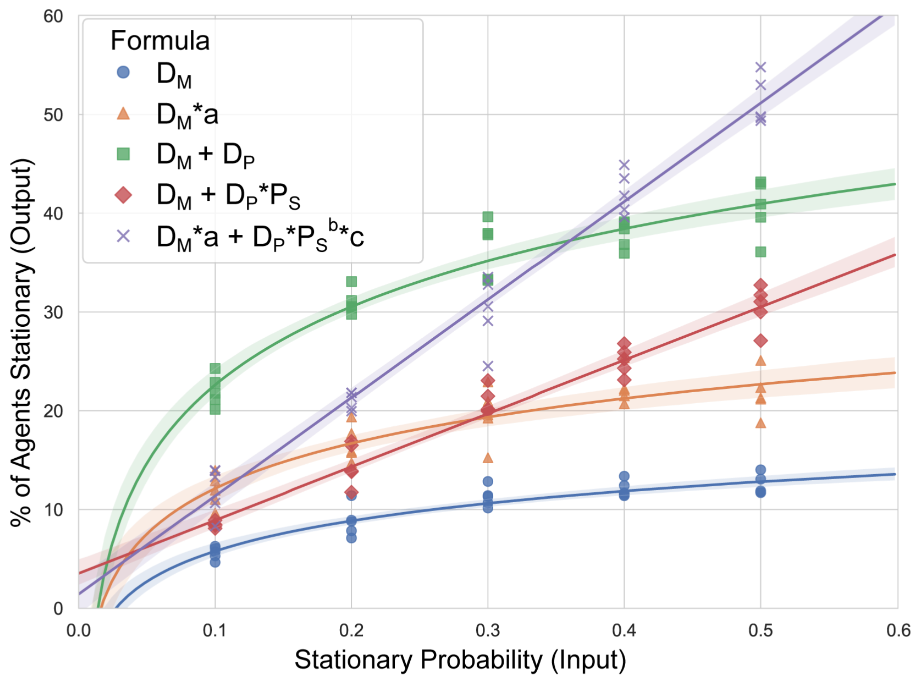


Figure 10: Agent population percentage engaged in stationary activity by different stationary activity probabilities, for different formulas of stationary activity duration calculation. The aim of the stationary activity duration calculation is to maintain consistency between model input and output, so that any input stationary activity probability is reflected in model output as the percentage of agents engaged in stationary activity, and therefore the aim is to implement a formula whose output falls on the diagonal in the graph.

3.7.6. Exit Process

When an agent enters its *Exit* process (either on its own after reaching the end of its visit, or due to the controller flagging it to exit prematurely, to regulate overall population numbers), it selects one of the area's gates at random, plans a path to it, and moves to its destination. Once the gate is reached the agent removes itself from the simulation.

4. Model experimentation

Testing and execution of the model was done using multiple different input parameter sets in order to establish two distinct tasks: Verify that the model performs as expected without significant bugs, and test the responsiveness of model output to input parameters through sensitivity analysis. Finally, once the model's internal mechanics had been tested thoroughly, the model's output was compared to spatial activity in open spaces as observed in other studies, to validate that the dynamics and spatial patterns exhibited by the model correspond to patterns exhibited in real world locations in similar conditions.

4.1. Experimental model setup

For the model test runs, the following model setup was implemented: The agent population was kept constant to 1000 agents for the duration of the run. The simulation duration was set to 21600 updates, equivalent to 6 hours in simulated time. For each parameter set, multiple simulation runs were performed. During each controller update a snapshot of the current state of the simulation was captured and relevant metrics were recorded.

The duration of the precalculation step for the *Social* activity was set to twice the average *Move* activity duration, with this value chosen as a balance between the agent covering adequate ground during sampling while at the same time not spending too much time to prepare for the stationary activity. Personal interaction distance for the *Social* activity was set to 10 meters. The area radius for the *Socio-Environmental* activity was set to 15 meters. View distance was set to 100 meters for all activities and sampling processes, with the exception of the angular-constrained random walks (ACRWs), where a modified value of 200 meters was also tested. Given that for some of these parameters no real-world data exists to validate against, the values mentioned here were set fairly arbitrarily to broadly correspond to real-world conditions, in order to provide a benchmark and some preliminary model results.

As stated in the model definition (subsection 3.4), agent lifetime was drawn from a probability table, with probabilities shown in Table 3. Lifetime is expressed in update ticks, which for this model correspond to seconds, i.e. the maximum visit duration (14400 seconds) is equivalent to 240 minutes/4 hours. Visit durations and probabilities were informed by park visitor surveys (Ipsos

Mori, 2015b,a).

Agent Lifetime (update ticks)	Probability
300 - 1800	0.16
1800 - 3600	0.24
3600 - 7200	0.39
7200 - 10800	0.16
10800 - 14400	0.04

Table 3: Agent Lifetime

Finally, agent movement speed values were drawn from a normal distribution with a mean of 1.49 m/s and a standard deviation of 0.15 m/s, with these values suggested by Daamen & Hoogendoorn (2007) as the characteristics of movement speeds of pedestrians moving in unconstrained conditions, which is an accurate description for conditions in a park.

4.2. Verification

As part of the model verification process, the variables not set explicitly to a single global value (i.e. those set by a probability table, drawn from distribution, etc) were tested to establish that model output does not deviate from intended distributions. Specifically, model verification was performed for agent population total, agent lifetime, and agent activity probabilities.

Agent population total over the course of the simulation is essentially a variable in the model, for multiple reasons: the controller does not have direct control over the removal of agents, but only sets the target population size and flags agents as necessary to run their 'Exit' behaviour if the target is exceeded; an agent's 'Exit' behaviour takes a variable amount of time, depending on distance to the exit, movement speed, etc; agents do not have a fixed lifetime, but rather their lifetime is decided by a probability table. For the reasons mentioned above then, agent population in the model is not guaranteed to always be consistent with the target agent population. As can be seen in Figure 11,

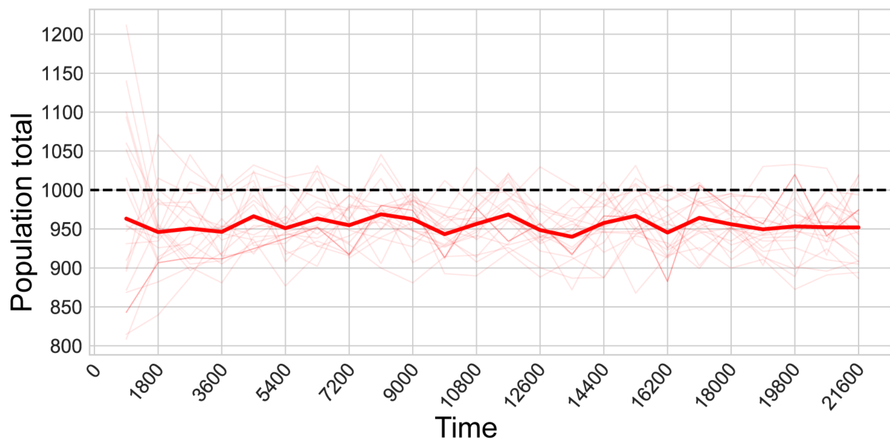
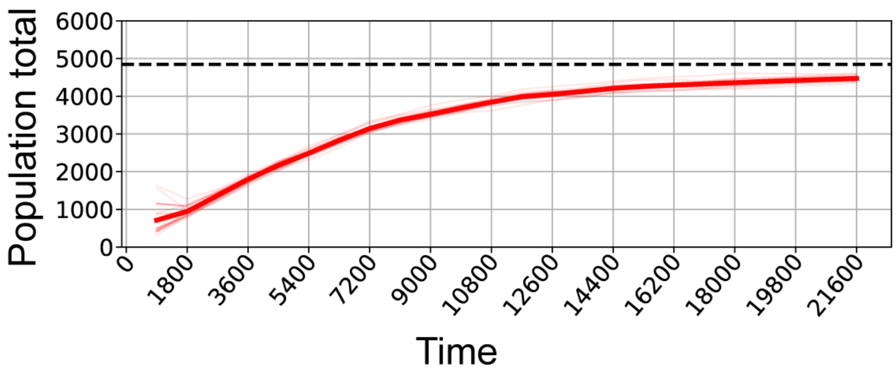


Figure 11: Agent population over time. Target population is marked by the bold dashed line.

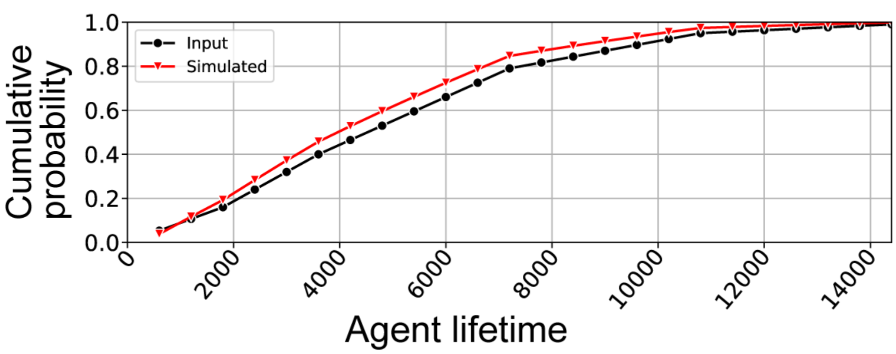
while the model performs well at keeping the agent population constant as expected, it consistently under-estimates by approximately 50 agents. This is due to the data logging process which takes place during the controller update when agent population is expected to be at its lowest, as agents introduced during previous updates have finished their lifetime and exited, but the controller has not introduced the new agents yet.

Agent average lifetime (representing park visit duration) was similarly logged over the course of the simulation run, calculated as the average lifetime of *all* agents in the simulation up until that point (including agents already removed from the simulation), and compared against the expected average visit duration form the probability table. As can be seen in Figure 12a, average agent lifetime converges to a value slightly less than the expected average of 4842 ticks, to 4445 ticks. Indeed by comparing cumulative probability curves for input and simulated lifetime averages (Figure 12b), it can be seen that the model slightly overestimates shorter lifespans.

Regarding agent activities, three aspects were examined: The average time per agent spent on any stationary activity compared to a movement activity; The average time spent engaged in a particular activity; And the relative number

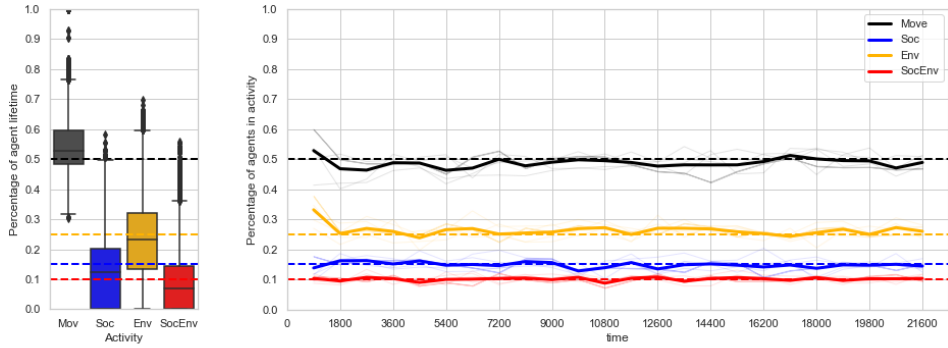


(a) Average agent lifetime over time. Expected average marked by bold dashed line



(b) Cumulative probability of agent lifetime

Figure 12: Average agent lifetime



(a) Percentage of lifetime spent in activity

(b) Percentage of agents engaged in activity over time

Figure 13: Agent activities. Dashed lines mark the expected value for each activity

of agents engaged in a particular activity at any point in the simulation. For this set of verification runs, the activity probabilities were set globally and were kept constant over the course of the simulation run, providing a homogeneous population regarding the agents' activity probabilities. Therefore the aim of the process here is to verify that activity probabilities perform as expected *on average* over all agents in the simulation.

For the verification run, the following activity probabilities were set arbitrarily, to check that agent activity durations are calculated as expected: Social activity $P_S = 0.15$, Environmental activity $P_E = 0.25$, Socio-Environmental activity $P_{SE} = 0.1$, and therefore the Move activity was assigned a probability of $P_M = 0.5$. Results from 5 simulation runs were recorded. Figure 13 shows the statistics of these runs, highlighting results relating both to the first two aspects, of activity durations regarding the *agent's* timeline, and the third aspect, of activity populations over the *simulation's* timeline.

As can be seen, on average the agents spend close to the expected amount of time in a particular activity (Figure 13a), however the model does appear to consistently under-estimate stationary activity durations slightly. In relation to the overall simulation however (Figure 13b), it appears that agents overall engage in activities as expected. This small discrepancy is attributed to agents with very short lifespans: In these instances the agent has not had enough time to engage in any activity (and therefore each of the activity percentages for the particular agent would be zero), and therefore is bringing the overall average activity duration over lifetime down, as it is calculated on a per-agent basis. Similarly, as these agents have a short lifespan, they are quickly removed from the simulation, and so they do not have time to have a significant impact on overall statistics over the course of the simulation.

4.3. Sensitivity analysis

In addition to verifying that model mechanics work as expected, the model was tested in regards to the impact different parameter values have on the overall output, as part of the model sensitivity analysis. This was done by inputting different parameter value ranges and recording model output for each in order to identify the effect of each, so that when the time comes for real-world data to be incorporated for calibration, operational ranges for model parameters are known along with their effects, allowing for a more controlled calibration. The following model parameters were tested: Agent vision distance (used solely for the *Move* activity), agent angle of view, and agent activity probabilities.

To visualize and measure the effect of different model parameters, a square grid of size 25 was implemented that was used to record the number of agents in each cell at regular intervals. Agents in each cell were recorded as a percentage of the agent population total at the current timestep, and were further categorized by the type of activity they were engaged in at that point. At the end of each simulation run, an average for each type of activity over all timesteps was taken for each activity type per cell, effectively producing a heatmap of activities aggregated over the course of the simulation, or in other words a footprint of activity distribution for each particular parameter set. The spatial distribution was visualized in two ways: with heatmaps using the grid values, preserving spatial relationships and allowing the spatial distribution to be understood in the context of the environment; and by plotting the cumulative sums of agent concentrations over ranked cell order using a Lorenz curve, so as to visualize the relative differences in agent concentrations, similar to the use of the curve in measuring the Gini index (Gastwirth, 1972).

4.3.1. Movement

Agent vision distance and agent angle of view values were examined for their impact on the wandering behaviour of agents. For the simulation runs examining these two particular parameters the agent stationary activity probabilities were set to zero, so that agents only engaged in wandering behaviours. Parameter values for the agent vision distance included the default value of 100 units and a doubled value of 200 units, while the angle of view parameter set included a 90° and a 180° angle. The two parameters were tested in combination, for a full set of 4 value combinations, with 5 simulation runs executed for each parameter combination.

An example of the spatial distribution of agents in the environment for each parameter combination is provided in Figure 14, to provide a better understanding of the spatial effects of each parameter value. Each image shows the cumulative agent densities for each cell at the end of the simulation run. Additionally, the Lorenz curve for each of the runs is shown in Figure 15, where a perfectly equal distribution (i.e. all cells containing an equal number of agents) would fall perfectly along the diagonal, and a larger curvature signifies a stronger disparity in agent concentrations between high and low density areas.

As can be seen in both figures, a shorter vision range results in a more smooth dispersion with less pronounced changes in density, whereas a longer vision range results in a sharp differentiation of more populated cells, found mainly on the paths and around bottlenecks. Angle of view has a less pronounced effect, positively affecting dispersion, but to a lesser degree. Both of these results are expected: Given the movement cost for navigating different terrains and the fact that paths are the preferred terrain for moving on, a longer vision distance allows agents to pick a destination that is further away, and therefore, their route-finding will have them on a path terrain for longer. Similarly, a wider

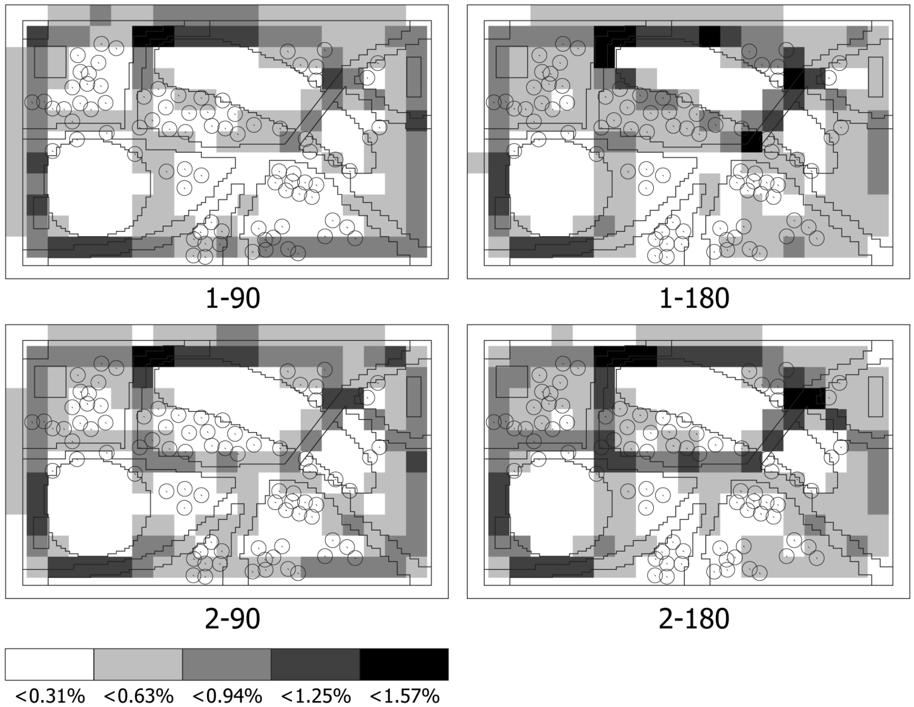


Figure 14: Agent distribution for *Movement* activity runs

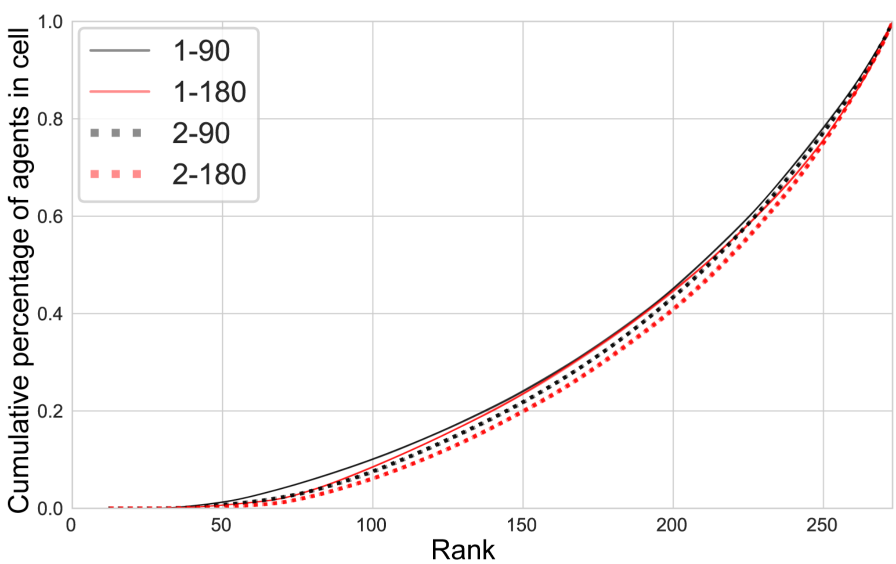


Figure 15: Grid cell occupation Lorenz curve for *Movement* activity runs

angle of view allows agents to pick targets that deviate more from their current heading. Also given the fact that most of the terrain is green areas, even in cases where an agent is heading down a path the likelihood of their random walk taking them into a green area is higher with a wider angle of view, an effect increased when in combination with a short vision distance, as the agent stays off-path for longer.

4.3.2. Stationary Activities

Stationary activity probabilities were examined for their impact on the distribution of agents in the environment. For the simulation runs examining activity probabilities, each activity was tested in isolation (essentially being the only stationary activity with a non-zero probability for that run), and furthermore each activity was tested at the 7.5% and 15% probability. For each parameter set, 3 simulation runs were performed. An example of the spatial footprint for each activity as well as the associated movement patterns is shown in Figure 16, which shows the result of each activity at a probability of 15%.

The Lorenz curves for each activity type and probability value, along with a set of 'no-activity' runs included for comparison, is shown in Figure 17. It is interesting to note a few things: For each of the activity types, an increase of the probability value results in a sharper difference in the concentrations between high and low density cells, in other words even at lower probabilities the agents detect and occupy the available and suitable areas, and increasing the probability of each activity increases the concentration of agents at those areas. However it is interesting to note that activity type does seem to affect the *range* of difference between high and low density areas, and furthermore the jump in difference appears to correlate with the degree to which an activity is tied to environmental parameters: The *Environmental* activity relies solely on environment parameters for an agent to engage in, and results in the largest increase in difference between low and high density areas when changing probability values, whereas the *Social* activity, which does not take into account environmental parameters, shows a negligible overall increase in difference. This finding makes

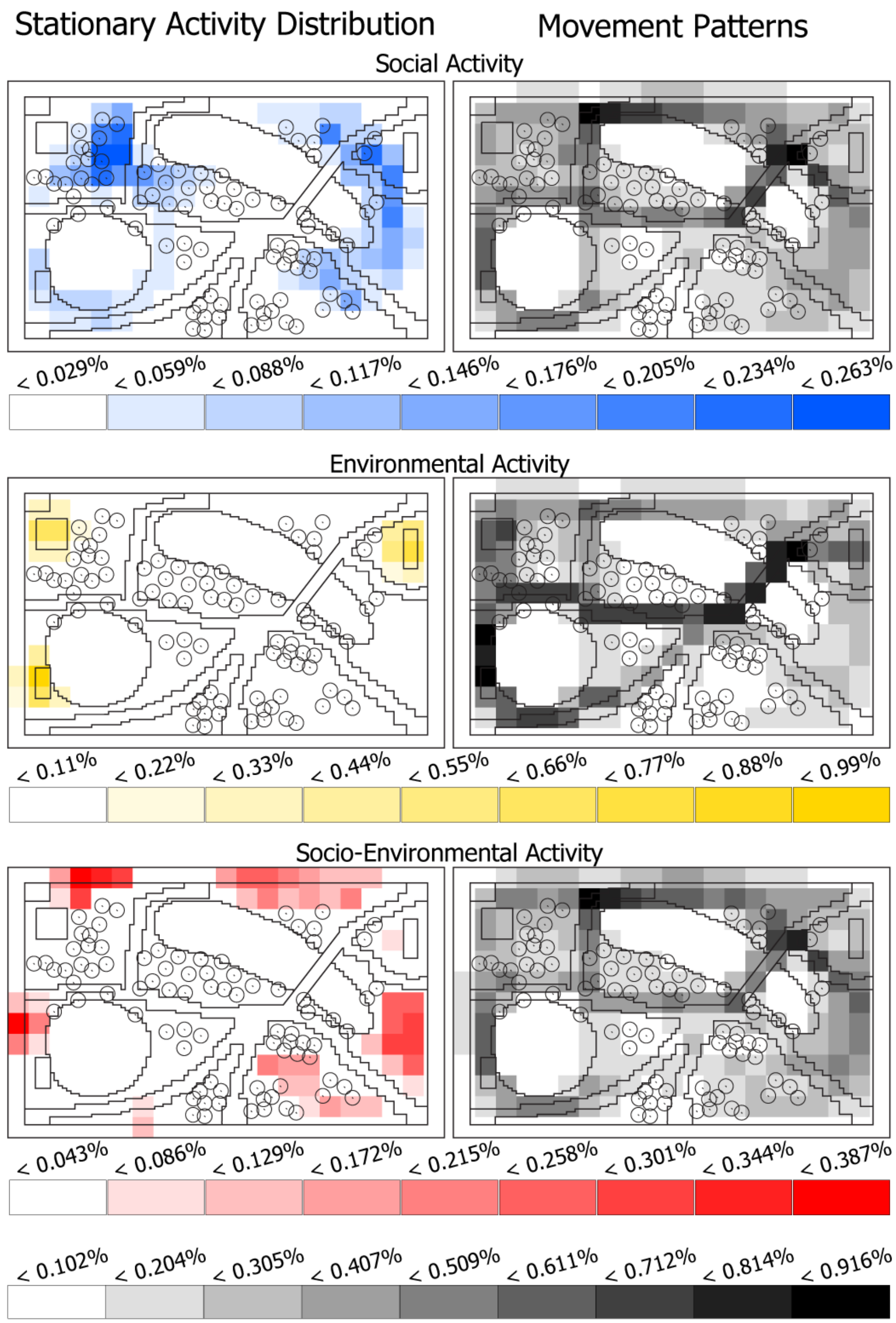


Figure 16: Agent distribution by activity for single *Stationary* activity simulation runs

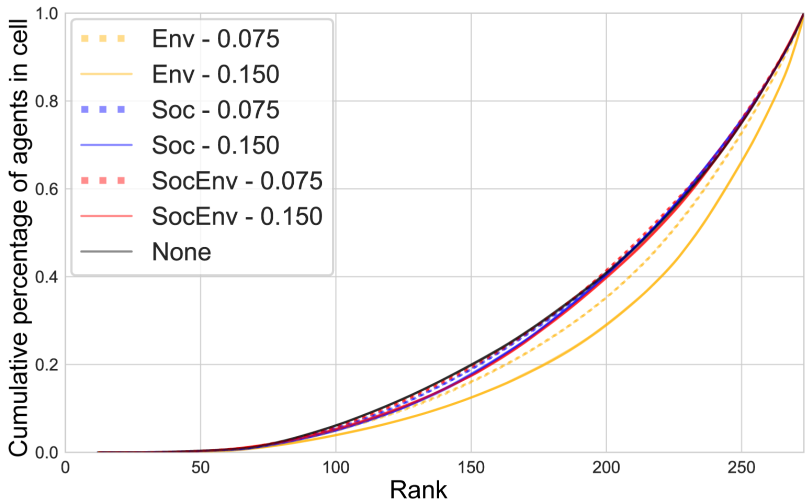


Figure 17: Grid cell occupation Lorenz curve for single *Stationary* activity simulation runs

sense: For activities that have a boundary restriction, i.e. can only happen within certain areas, increasing the population of agents engaging in such activities only increases the density/concentration at those certain areas, whereas activities that are not bound spatially are allowed to spill over to other, less optimal locations, if needed.

4.4. Validation

An extended validation of this model against real-world data captured specifically for this task is outside the scope of this paper, whose aim was to present the model mechanics. In lieu of validation, a number of patterns as generated in the model are compared to behavioural patterns captured in previous studies, to demonstrate that in principle the model of public space use is able to generate behavioural patterns similar to those found in the real-world.

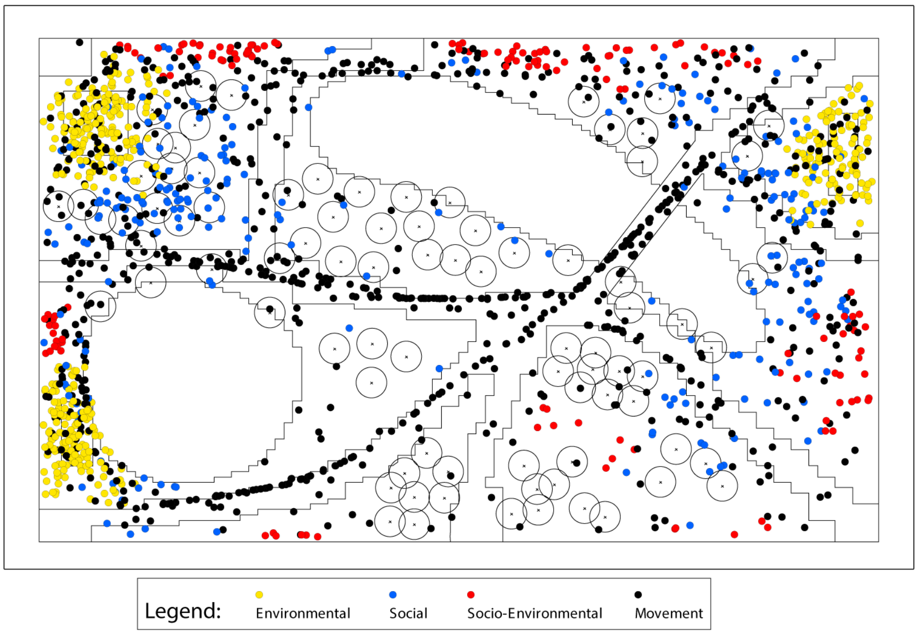
Spatial distributions of activity were compared to recorded activity in a park in Edinburgh as reported by Goličnik & Ward Thompson (2010) (Figure 18). The model appears to present similar clustering effects to the empirical study, particularly when comparing observed sport and play activities to simulated *Socio-Environmental* activity: in both cases, the activity appears to take over open areas in the park, and furthermore has minimal overlap with other activities[5]. Visitors on the move appear to predominantly stay on paths, both in the model and in the empirical study, although in the model agents moving towards a location to engage in a stationary activity are classified as being in a *Move* state, and therefore a number of them is also recorded away from paths. *Social* activities, although under-represented in the empirical study (only a single activity type was recorded, of visitors *sitting*), nevertheless appear to have similar characteristics to the distribution of simulated *Social* activity: the few clusters of *sitting* visitors are out of the way of *Socio-Environmental*/sports activities, and are near and within view of larger crowds. Finally, regarding the *Environmental* activity, the empirical study does not present observations on location-specific activities, as the area itself (the Meadows) do not contain significant features that could be considered as attractors in the sense used in this model, and therefore this activity could not be validated.

Movement as well as temporal patterns of simulated visitor behaviours were compared to similar patterns as reported by other studies. Orellana et al. (2012) present movement patterns of four visitors to a national recreational area, analysing their sequence of visited locations and time spent on each from a list of attractions, quite similar to this model's implementation of an *Environmental* activity. Simulated movement tracks of four agents (Fig. 19a) present a similar pattern, with fixed attractor locations showing significantly increased concentrations of visitation, and furthermore with agent tracks tracing out major pathways between the locations (highlighted in yellow). One major difference is noted however compared to observed paths (as shown in Fig. 19b), in that simulated paths are significantly more scattered throughout the area: this is due to two factors, first the ACRW movement behaviour in agents causes them to randomly wander in the area when not moving towards a goal, and second

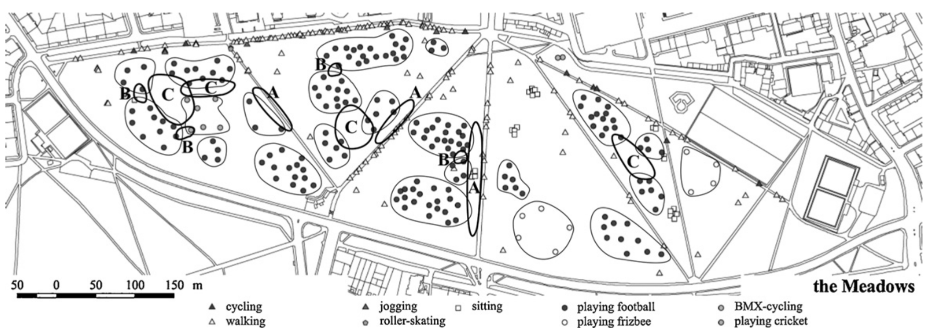
[5]In the model, movement activities are not considered as obstacles when an agent is searching for a location for a *Socio-Environmental* activity, and therefore overlap between *SE* and movement activities is not considered

the inclusion of other stationary activities which take place at locations other than attractor points.

Similarly, temporal patterns of four agents were compared to visit sequences of visitors from the same study. The empirical study used here for validation (Orellana et al., 2012) focussed on capturing visit sequences between distinct locations and the order in which they were visited, which is outside the scope of the model presented here, as agents choose locations at random. However, what is of interest is the similarities in temporal patterns when considering model *Environmental* activity: the long timespans between locations in some cases (e.g. visitor C from location 1 to 2 and visitor D in Fig. 19d, compared to agents B and D in Fig. 19c), as well as the visits to locations done in rapid succession (e.g. visitors A, B in 19d, compared to agent A in Fig. 19c). A significant difference is seen however in the durations of visits/stationary activities: while observed visits seem to last anywhere from 15 minutes to over an hour, simulated activity durations appear more homogeneous, lasting approximately 330 update ticks with little variation. Although this is expected, as activity durations were not calibrated to real-world data, it nevertheless highlights a limitation of the model's current implementation, when examined at the level of individual visitors. Therefore, while the proposed model seems to successfully capture activity *in aggregate* it is less accurate on an individual basis, a common characteristic of ABMs, whose aim is to reproduce a system's patterns of behaviour *on the whole* through simple individual rules.

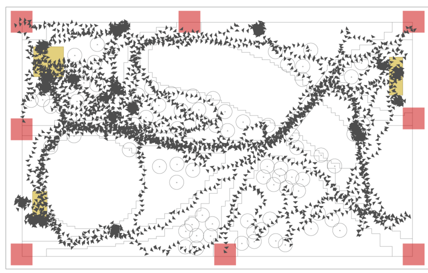


(a) Simulated

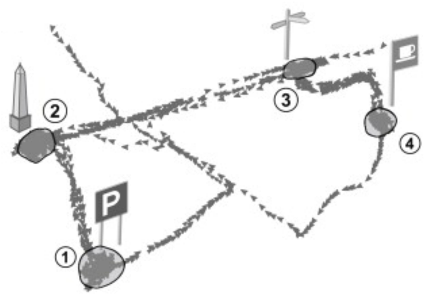


(b) Observed

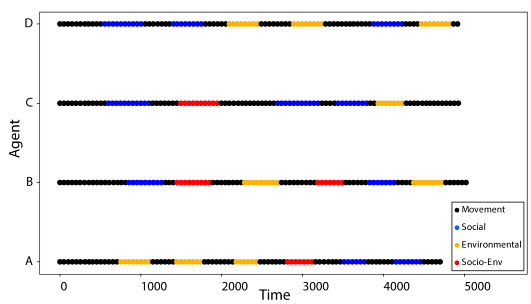
Figure 18: Activity spatial pattern validation (Figure 18b from Fig. 11 in (Goličnik & Ward Thompson, 2010))



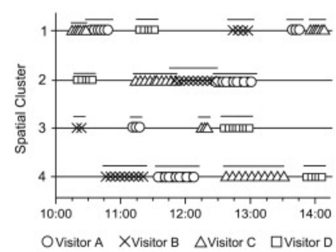
(a) Simulated Paths



(b) Observed Paths



(c) Simulated Timelines



(d) Observed Timelines

Figure 19: Agent path and timeline validation (Figures 19b, 19d from Fig. 2 in (Orellana et al., 2012))

5. Conclusions

This paper highlighted recent advances in the study of human spatial behaviour through computational simulation, and identified limitations in existing computational analytical tools in design. In response, it presented an agent-based model (ABM) of public space use, built using existing observations and findings on public space use, and presented using the Overview, Design Concepts, and Details (ODD) protocol, a widely accepted protocol for presenting ABMs.

This paper presented a review of related methodologies within the scope of spatial design and human spatial behaviour, highlighting the deterministic approach of some, the narrow focus on crowd flows of others, and some existing individual and agent-based models of space use. However limitations were identified in reviewed approaches, which this research aims to account for. Whereas similar approaches have focussed on simulating specific user behaviour related to the environment of interest, this work aimed at providing a more formalized model of human spatial behaviour in open spaces. By incorporating observations on public space use and encoding them in abstract form, this work presents a generalized model of collective human spatial behaviour, such that may be more easily extended, and designed so that it may be more easily calibrated to specific scenarios.

Multiple simulation tests were performed to verify that the model works as expected, and to test its responsiveness to input parameters. Although the model was presented through application to a synthetic environment and therefore could not be fully calibrated and validated against real-world data, nevertheless it was tested and found to perform consistently and to provide accurate outputs, in line with expected results and inputs. Furthermore, a concise input parameter sweep was performed to examine the impact of input parameter values to model output, and simulation output was measured via Lorenz curves capturing the spatial dispersion of activity and the degree to which agent population is unequally distributed, allowing for a more meaningful comparison of results. Finally, model output was compared to observed activity patterns in other studies of similar spaces, and simulated spatial activity patterns were found to match those observed in real-world scenarios.

The model was designed and implemented in three-dimensional space using simplified mesh geometry and volumetric colliders. Due to the scale of observation of the field of interest, that being the field of architectural and urban design, the inclusion of three-dimensional space was considered imperative for the accurate representation of space and human spatial behaviour at this scale, as it provides a more natural description of the system of interest, and can better accommodate the particularities of three-dimensional spatial relationships and interactions between humans in space (Cheliotis, 2019). Although 3D models of space offer the potential for significantly detailed visualisations, more simplified 3D geometry was used here for reasons of computational efficiency.

Future work will move in multiple fronts, as enabled by the flexibility of the ABM paradigm: First of all, as this model was presented using a sample synthetic environment, no data existed for a meaningful calibration and validation of the model. However, its output and generated patterns of behaviour were shown to be in line with results from existing behavioural mapping studies. As such follow-up work will focus on calibrating the model by applying to real-world scenarios using data collected through site surveys of parks and open urban spaces.

Additionally, as the overall model of public space activity is constructed as a combination of sub-models of specific human tasks, these may be updated independently by incorporating more advanced approaches, for example by including more informed path-finding or movement strategies at the individual agent level. Finally, the model presented abstracted implementations of agent activities, aiming for a more generalized framework of human spatial behaviour, but still stemming from typical behaviours in public open spaces. In this vein, further research will be undertaken to identify additional spatial behaviours and extend existing activity types, so as to expand the model scope to other spatial configurations and environments.

This type of model provides benefits to researchers investigating human spatial behaviour in general, and may further provide a useful tool for scenario exploration for practitioners and designers of spatial environments (architects, urban designers), allowing them to assess the expected impact of design decisions on user activity *during* the design stage. The next stage of this work is to streamline the environment setup process, to allow additional environments to be examined and expand the scope of application.

References

Angus, S. D., & Hassani-Mahmooei, B. (2015). "Anarchy" Reigns: A Quantitative Analysis of Agent-Based Modelling Publication Practices in JASSS, 2001-2012. *Journal of Artificial Societies and Social Simulation*, *18*, 16.

Bafna, S. (2003). Space Syntax: A Brief Introduction to Its Logic and Analytical Techniques. *Environment and Behavior*, *35*, 17–29. doi:10.1177/0013916502238863.

Batty, M., Desyllas, J., & Duxbury, E. (2003). Safety in Numbers? Modelling Crowds and Designing Control for the Notting Hill Carnival. *Urban Studies*, *40*, 1573–1590. doi:10.1080/0042098032000094432.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, *99*, 7280–7287. doi:10.1073/pnas.082080899.

Castle, C. J. E., Waterson, N. P., Pellissier, E., & Bail, S. L. (2011). A Comparison of Grid-based and Continuous Space Pedestrian Modelling Software: Analysis of Two UK Train Stations. In R. D. Peacock, E. D. Kuligowski, & J. D. Averill (Eds.), *Pedestrian and Evacuation Dynamics* (pp. 433–446). Springer US.

Cheliotis, K. (2019). *Agent-Based Modelling of Public Space Activity in Real-Time*. Doctoral Thesis UCL (University College London).

Crooks, A., Croitoru, A., Lu, X., Wise, S., Irvine, J. M., & Stefanidis, A. (2015). Walk This Way: Improving Pedestrian Agent-Based Models through Scene Activity Analysis. *ISPRS International Journal of Geo-Information*, *4*, 1627–1656. doi:10.3390/ijgi4031627.

Daamen, W., & Hoogendoorn, S. P. (2007). Free speed distributions — Based on empirical data in different traffic conditions. In N. Waldau, P. Gattermann, H. Knoflacher, & M. Schreckenberg (Eds.), *Pedestrian and Evacuation Dynamics 2005* (pp. 13–25). Springer Berlin Heidelberg.

Dursun, P. (2007). Space syntax in architectural design. In *6th International Space Syntax Symposium* (pp. 01–56).

Gastwirth, J. L. (1972). The Estimation of the Lorenz Curve and Gini Index. *The Review of Economics and Statistics*, *54*, 306–316. doi:10.2307/1937992.

Gehl, J. (1987). *Life between Buildings: Using Public Space*. New York: Van Nostrand Reinhold.

Gehl Architects (2004). *Towards a Fine City for People, Public Space, and Public Life - London 2004*. Copenhagen: Gehl Architects.

Gilbert, N. (2007). *Agent-Based Models*. (annotated edition edition ed.). Los Angeles: SAGE Publications, Inc.

Goličnik, B. (2005). *People in Place : A Configuration of Physical Form and the Dynamic Patterns of Spatial Occupancy in Urban Open Public Space*. Ph.D. thesis.

Goličnik, B., & Ward Thompson, C. (2010). Emerging relationships between design and use of urban park spaces. *Landscape and Urban Planning*, *94*, 38–53. doi:10.1016/j.landurbplan.2009.07.016.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S. K., Huse, G., Huth, A., Jepsen, J. U., Jørgensen, C., Mooij, W. M., Müller, B., Pe'er, G., Piou, C., Railsback, S. F., Robbins, A. M., Robbins, M. M., Rossmanith, E., Rüger, N., Strand, E., Souissi, S., Stillman, R. A., Vabø, R., Visser, U., & DeAngelis, D. L. (2006). A standard protocol for describing individual-based and agent-based models. *Ecological Modelling*, *198*, 115–126. doi:10.1016/j.ecolmodel.2006.04.023.

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., & Railsback, S. F. (2010). The ODD protocol: A review and first update. *Ecological Modelling*, *221*, 2760–2768. doi:10.1016/j.ecolmodel.2010.08.019.

Hadjri, K., & Crozier, C. (2009). Post-occupancy evaluation: Purpose, benefits and barriers. *Facilities*, *27*, 21–33. doi:10.1108/02632770910923063.

Helbing, D., & Molnár, P. (1995). Social force model for pedestrian dynamics. *Physical Review E*, *51*, 4282–4286. doi:10.1103/PhysRevE.51.4282.

Heppenstall, A., Malleson, N., & Crooks, A. (2016). "Space, the Final Frontier": How Good are Agent-Based Models at Simulating Individuals and Space in Cities? *Systems*, *4*, 9. doi:10.3390/systems4010009.

Hillier, B. (2007). *Space Is the Machine: A Configurational Theory of Architecture*. London, UK: Space Syntax.

Hong, S. W., Schaumann, D., & Kalay, Y. E. (2016). Human behavior simulation in architectural design projects: An observational study in an academic course. *Computers, Environment and Urban Systems*, *60*, 1–11. doi:10.1016/j.compenvurbsys.2016.07.005.

Ipsos Mori (2015a). *Royal Parks Stakeholder Research Programme 2014 - Park Profile: Hyde Park (Waves 1-3)*. Technical Report The Royal Parks.

Ipsos Mori (2015b). *Royal Parks Stakeholder Research Programme 2014 - Park Visitors Research*. Technical Report The Royal Parks.

Ittelson, W. H. (1970). *The Use of Behavioral Maps in Environmental Psychology*.

Jacobs, J. (1961). *The Death and Life of Great American Cities*. Knopf Doubleday Publishing Group.

Juliani, A., Berges, V.-P., Vckay, E., Gao, Y., Henry, H., Mattar, M., & Lange, D. (2018). Unity: A General Platform for Intelligent Agents. *arXiv:1809.02627 [cs, stat]*, . arXiv:1809.02627.

Karimi, K. (2012). A configurational approach to analytical urban design: 'Space syntax' methodology. *URBAN DESIGN International*, *17*, 297–318. doi:10.1057/udi.2012.19.

Koutsolampros, P., Sailer, K., & Varoudis, T. (2018). Partitioning indoor space using visibility graphs: Investigating user behavior in office spaces. In *Proceedings of 4th International Symposium Formal Methods in Architecture - 2018*.

Ng, C. F. (2016). Behavioral Mapping and Tracking. In *Research Methods for Environmental Psychology* (pp. 29–51). John Wiley & Sons, Ltd. doi:10.1002/9781119162124.ch3.

Orellana, D., Bregt, A. K., Ligtenberg, A., & Wachowicz, M. (2012). Exploring visitor movement patterns in natural recreational areas. *Tourism Management*, *33*, 672–682. doi:10.1016/j.tourman.2011.07.010.

Papadimitriou, E., Yannis, G., & Golias, J. (2009). A critical assessment of pedestrian behaviour models. *Transportation Research Part F: Traffic Psychology and Behaviour*, *12*, 242–255. doi:10.1016/j.trf.2008.12.004.

Pelechano, N., Allbeck, J. M., & Badler, N. I. (2007). Controlling individual agents in high-density crowd simulation. In *Proceedings of the 2007 ACM SIGGRAPH/Eurographics Symposium on Computer Animation* SCA '07 (pp. 99–108). Aire-la-Ville, Switzerland, Switzerland: Eurographics Association.

Pelechano, N., Allbeck, J. M., & Badler, N. I. (2008). Virtual Crowds: Methods, Simulation, and Control. *Synthesis Lectures on Computer Graphics and Animation*, *3*, 1–176. doi:10.2200/S00123ED1V01Y200808CGR008.

Penn, A. (2003). Space Syntax And Spatial Cognition: Or Why the Axial Line? *Environment and Behavior*, *35*, 30–65. doi:10.1177/0013916502238864.

Penn, A., & Turner, A. (2001). Space syntax based agent simulation. In *Presented at: 1st International Conference on Pedestrian and Evacuation Dynamics, University of Duisburg, Germany. (2001)*. University of Duisburg, Germany.

Sailer, K., Koutsolampros, P., Austwick, M. Z., Varoudis, T., & Hudson-Smith, A. (2016). Measuring Interaction in Workplaces. In *Architecture and Interaction* Human-Computer Interaction Series (pp. 137–161). Springer, Cham. doi:10.1007/978-3-319-30028-3_7.

Sailer, K., & McCulloh, I. (2012). Social networks and spatial configuration—How office layouts drive social interaction. *Social Networks*, *34*, 47–58. doi:10.1016/j.socnet.2011.05.005.

Schaumann, D., Kalay, Y. E., Hong, S. W., & Simeone, D. (2015). Simulating Human Behavior in Not-yet Built Environments by Means of Event-based Narratives. In *Proceedings of the Symposium on Simulation for Architecture & Urban Design* SimAUD '15 (pp. 5–12). San Diego, CA, USA: Society for Computer Simulation International.

Schaumann, D., Pilosof, N. P., Date, K., & Kalay, Y. E. (2016). A study of human behavior simulation in architectural design for healthcare facilities. *Annali dell'Istituto Superiore di Sanità*, *52*, 24–32.

Simeone, D., & Kalay, Y. E. (2012). An Event-Based Model to simulate human behaviour in built environments. In *Digital Physicality: Proceedings of the 30th eCAADe Conference* (pp. 525–532). Prague, Czech Republic: Czech Technical University in Prague, Faculty of Architecture volume 1 of *eCAADe: Conferences*.

Torrens, P. M. (2015). Intertwining agents and environments. *Environmental Earth Sciences*, *74*, 7117–7131. doi:10.1007/s12665-015-4738-3.

Torrens, P. M. (2016). Computational Streetscapes. *Computation*, *4*, 37. doi:10.3390/computation4030037.

Turner, A. (2007). From Axial to Road-Centre Lines: A New Representation for Space Syntax and a New Model of Route Choice for Transport Network Analysis. *Environment and Planning B: Planning and Design*, *34*, 539–555. doi:10.1068/b32067.

Unity Technologies (2018). Unity - Manual: Unity User Manual (2018.2). https://docs.unity3d.com/Manual/index.html.

Whyte, W. H. (1980). *The Social Life of Small Urban Spaces*. Conservation Foundation.

Wurzer, G., Popov, N., & Lorenz, W. E. (2012). Meeting Simulation Needs of Early-Stage Design Through Agent-Based Simulation. In *Digital Physicality: Proceedings of the 30th eCAADe Conference* (pp. 613–620.). Prague, Czech Republic: Czech Technical University in Prague, Faculty of Architecture volume 1 of *eCAADe: Conferences*.

Yan, W. (2008). Environment-Behavior Simulation: From CAD to BIM and Beyond. In *Silicon + Skin: Biological Processes and Computation, [Proceedings of the 28th Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA) / ISBN 978-0-9789463-4-0] Minneapolis 16-19 October 2008, 478-485*. CUMINCAD.

Yan, W., & Forsyth, D. A. (2005). Learning the Behavior of Users in a Public Space through Video Tracking. In *Seventh IEEE Workshops on Application of Computer Vision, 2005. WACV/MOTIONS '05 Volume 1* (pp. 370–377). volume 1. doi:10.1109/ACVMOT.2005.67.

Yan, W., & Kalay, Y. (2005). Simulating Human Behaviour in Built Environments. In *Computer Aided Architectural Design Futures 2005 [Proceedings of the 11th International Conference on Computer Aided Architectural De-*

sign Futures / ISBN 1-4020-3460-1] Vienna (Austria) 20–22 June 2005, Pp. 301-310. CUMINCAD.

Yan, W., & Kalay, Y. E. (2004). Simulating the Behavior of Users in Built Environments. *Journal of Architectural and Planning Research*, *21*, 371–384.

Zhang, X., Schaumann, D., Haworth, B., Faloutsos, P., & Kapadia, M. (2019). Coupling agent motivations and spatial behaviors for authoring multiagent narratives. *Computer Animation and Virtual Worlds*, *30*, e1898. doi:10.1002/cav.1898.

Zimring, C. M., & Reizenstein, J. E. (1980). Post-Occupancy Evaluation: An Overview. *Environment and Behavior*, *12*, 429–450. doi:10.1177/0013916580124002.