Privacy-Aware Agent-Based Simulation for Modeling Indoor Movement Patterns in University Campuses

Master thesis
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Faculty of Spatial Sciences
University of Groningen

Elmeri Niemi
Student number: S3783723

Supervisor: Gerd Weitkamp, PhD

Abstract

This master thesis explores the development of a privacy-conscious methodology for modeling indoor movement patterns in campus environments using Agent-Based Simulation (ABS). The primary research question addresses how movement can be accurately modeled while ensuring the privacy of individuals. The study utilizes WiFi-based occupancy data and an adapted PageRank algorithm to predict movement behaviors within university buildings without individual tracking. The ABS model incorporates various factors, including agent ontologies, room attractiveness, and spatial relationships, to simulate realistic indoor movement patterns. The model is validated using real-world data from the University of Groningen, demonstrating strong correlation between simulated and observed building occupancy. The findings highlight the effectiveness of the methodology in replicating movement patterns across different areas of the building, though some areas required further refinement. The use of aggregate data ensures privacy preservation, successfully balancing the need for data-driven insights with ethical data practices. This research contributes a novel approach to the field of indoor spatial analysis, with practical applications for space management, energy efficiency, and campus planning. The flexible framework developed can be adapted to various indoor environments, offering significant potential for future research and implementation.

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Acknowledgement

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1 Introduction

In university campuses, the days start with groups of people rushing in to lectures and to work, continuing in complex patterns throughout the day. Students go to lectures, after which they head for lunch together, while employees go get coffee in their offices. We can observe these patterns with our own eyes, and we have a feel of how to move around the building. Instead of a feeling, what if we had data on hand so we can act on it and make better decisions for space management?

Understanding these movement patterns has become more and more important in the age of sustainability which necessitates more and more effective space management in campus environments. This importance thus extends beyond the academic world where these methods are used to generate data for mobility research or other studies looking that need data about indoor movement, as knowing these patterns not only will help facility managers save in costs by making their space use more efficient, but allows us to have a view of how might the movement in buildings change based on the composition of user groups and activities, giving a detailed understanding of how people navigate and utilize different areas. This knowledge can inform a wide range of decisions, from optimizing classroom schedules and designing more intuitive building layouts to implementing smarter resource allocation strategies (Kim et al., 2013).

Despite the importance of understanding indoor movement patterns to enhance space management and efficiency, hard data is often left out of the conversation due to privacy-related concerns, especially on university campuses (White et al., 2021). Studies have shown that detailed data on occupancy and movement can lead to significant cost savings and sustainability improvements in campus facilities (Valks et al., 2019; Azizi et al., 2020). However, the collection of such data raises valid concerns about individual privacy, particularly in sensitive settings like universities (White et al., 2021). This tension between the need for data-driven decision making and the protection of personal information must be carefully navigated to unlock the full potential of indoor movement analysis.

Traditional methods for tracking and analyzing indoor movement often rely on invasive data collection techniques, such as video surveillance or individual tracking devices (Stojanović & Stojanović, 2014). While these approaches can provide high-resolution data, they raise significant privacy concerns and may alter natural behaviour patterns due to the awareness of being monitored. Moreover, they fail to capture the full complexity of human movement behaviour, which is influenced by a collection of factors including personal preferences, social interactions, and environmental context.

This research addresses the pressing need for a privacy-conscious methodology to model and predict indoor movement patterns using Agent-Based Simulation (ABS). The study focuses on understanding how occupancy counts, contextual data, and the attractiveness of rooms—modeled through a modified PageRank algorithm can predict real-time movement behaviours within university buildings, enhancing the effectiveness of spatial design and planning.

The novelty of this approach lies in its unique combination of methodologies. While ABS has been used in various spatial contexts, its application to indoor movement in campus environments, particularly with a focus on privacy, is relatively unexplored. By adapting the PageRank algorithm to spatial contexts, this research allows for a nuanced understanding of room "importance" based on connectivity and occupancy patterns. Furthermore, by relying on aggregate data (e.g., WiFi-based occupancy counts) rather than individual tracking, this study demonstrates how meaningful insights can be derived while respecting user privacy. The integration of various contextual elements such as time of day, room types, and scheduled events provides a more holistic representation of the factors influencing movement. To address the core problem of accurately predicting and optimizing indoor movement patterns while ensuring individual privacy, this research utilises the following research questions:

Main RQ: How can indoor movement patterns be modeled in campus environments while ensuring the privacy of individuals?

SubQ1: What type of agent ontology can be best applied to guide agent movement behaviour?

SubQ2: How to model attractiveness of rooms in spatio-temporal context using Geographical PageRank?

SubQ3: What role do distance and other spatial factors play in modeling indoor behaviour?

The methodology employed in this research is composed of five parts. It begins with the collection of aggregate WiFi-based occupancy data and building schedules, ensuring privacy by avoiding individual tracking. A custom ABS model is then developed, incorporating various agent types (e.g., students, staff) with specified behavioural patterns based on their type. The adapted PageRank algorithm is implemented to model room attractiveness based on connectivity and occupancy. Finally, the model is validated against real-world occupancy data, ensuring its accuracy in predicting movement patterns.

This research aims to contribute to the field of indoor spatial analysis and campus management in several ways. It offers a novel, privacy-conscious methodology for modeling indoor movement patterns, provides insights into the factors influencing movement within campus buildings, and presents a flexible framework that can be adapted to various indoor environments. The practical implications of this work extend to space management, energy efficiency, and campus planning.

1.1 Literature review

1.1.1 Understanding indoor movement dynamics

The efficient management of indoor spaces hinges on a comprehensive understanding of occupant movement patterns. Research consistently underscores the significance of modeling indoor movement for optimizing space utilization, addressing safety concerns, and enhancing the overall experience within built environments (Arslan et al., 2019; Valks et al., 2018; Valks et al., 2019). Traditional tracking methods often involve intrusive data collection or oversimplifications of complex human behaviours. This highlights the need for innovative approaches that prioritize privacy while accurately capturing real-world movement dynamics.

1.1.2 Privacy-conscious methodologies

The growing emphasis on privacy in smart building solutions has led to a critical examination of data collection practices. Studies underscore the importance of non-invasive methods for occupancy monitoring, especially in sensitive environments like university campuses (Ahmad et al., 2021; Sun et al., 2021). Techniques such as coarse-grained WiFi-based occupancy detection, while respecting privacy, might lack the granularity to model detailed movement patterns effectively (Zakaria et al., 2022). There is a crucial need to develop methodologies that achieve a balance between data-driven insights and ethical data practices.

1.1.3 Agent-based simulation for spatial modeling

Agent-Based Simulation (ABS) has emerged as a powerful tool for modeling complex systems and spatial behaviours within various domains. Its capacity to represent individual entities (agents) and their interactions with each other and the space they are moving in makes it well-suited for simulating indoor movement patterns (Torrens et al., 2012). Research demonstrates the flexibility of agent architectures in ABS, allowing for diverse agent behaviour models that enhance the realism and adaptability of simulations in spatial design and planning (Pax & Pavón, 2017). While there has been little usage of agent-based simulation models in indoor environments, multiple authors demonstrate its usefulness in a node network represented by a graph, which essentially shares the same characteristics as indoor networks modified into a graph. A graph for indoor environments is only a smaller version of a graph made for outdoor environments. In this part of the literature review I aim to highlight how this type of modeling has been used in these networks, and how adding contextual factors such as routes, or probabilities based on activity type can enhance the spatial modeling. As an example, agent-based simulation has been combined with route choice solutions, modeling dynamic movement patterns in various use cases, such as traffic modeling (Klügl & Rindsfüser, 2011; Kaziyeva et al., 2021; Zhao et al., 2019), of only the latter of which doesn't add contextual factors, and crowding in shopping malls (Dijkstra & Jessurun, 2014).

Klügl and Rindsfüser (2011) proposed MoRou, an agent-based simulation model that allows agents to navigate a network to reach events. The model is grounded in objective real-world data such as network topology, bus schedules, and other environmental factors. Each agent in the model has an origin-destination pair and evaluates the best route based on its past experiences. The authors demonstrate that incorporating data associated with routes enables the enhancement of agent-based simulations, improving the effectiveness of signage planning.

Kaziyeva et al. (2021) developed an agent-based model to simulate bicycle usage patterns in Salzburg, involving a diverse population of 186,000 individuals over a simulated day. The agents in their model are assigned actions that specify what they should do, when, with what mode, and the corresponding route. The target facilities possess contextual information, and the selection of options is based on probability distributions. The model logs the agents' positions and actions at regular intervals. The authors underscore the superiority of well-parameterized models over stochastic models in this context. While the model effectively captures the temporal timing of flows, the accuracy of flow patterns might be limited by the availability of verification data. Nevertheless, the study highlights the utility of agent-based simulation in predicting cyclist flows on real-world road networks and emphasizes the significance of activity assignment in model performance.

In a different setting, Zhao et al. (2019) created an agent-based macroscopic traffic simulation model in San Francisco. The model assigns an agent to each origin-destination pair within the travel demand and operates in hourly steps. To determine optimal routes for each agent, the model employs a priority-queue-based Dijkstra algorithm. It dynamically adjusts link-level travel times and produces traffic simulations consistent with real-world data.

Agent-based simulation modeling has also been used specifically in indoor environments. Dijkstra & Jessurun (2019) proposed an architecture for agents that uses some form of steering for their behaviour. Their main findings showed that adding contextual information about the environment and activities allowed the agents to move better in the built environment. The authors also showed how empirical data collected about movement can be used to tune the parameters for the agent based simulation.

1.1.4 Agent ontology in agent-based simulation

Raubal (2001) describes ontologies for agent-based simulation for wayfinding. The ontologies are essentially the underlying beliefs that are attributed to each agent that guide their actions, and the real-world states that are assigned to the environment in the simulation. Raubal (2001) describes a model for a "cognizing agent", that is a rational actor with access to information about the environment. The work also sets a plan for agent movement, based on sensing the environment, planning the following actions and then moving, i.e. acting upon the action. The research concludes with a mention of how a well defined ontology allows for simulation in a way that is realistic. Bhattacharya et al. (2013), created a framework for agent-based modeling, focusing on spatial movements generated based on two distinct ontologies. The first ontology covers outdoor behaviours, identifying landmarks and behaviour attributes relevant in an outdoor setting. The indoor agent ontology includes factors such as indoor space characteristics and descriptive indoor behaviour attributes as a way of creating a model of understanding for the agent. Arslan et al. (2019) proposed the OBiDE (Occupancy behaviour in Dynamic Environments) framework, which offers a structured approach for understanding occupant behaviour in relation to contextual information (Arslan et al., 2019). They propose the DNAS (drivers, needs, actions and systems) ontology for contexts, where it's crucial to understand occupant behaviour. They reiterate the importance of contextual information about the environment itself, and how it can impact modeling occupant behaviour. Their research proposed an approach on how to integrate this information into models, and concluded by providing a semantic enrichment model to integrate this information.

1.1.5 Movement behaviour

A framework and movement analysis taxonomy to consider is by Andrienko et al. (2011), who introduce a conceptual framework and taxonomy for analyzing movement. Their approach categorizes movement analysis tasks into elemental and synoptic types, which directly supports the simulation of individual and collective behaviours within complex indoor spaces like university campuses. Geographical PageRank and Context-Aware Movement Geographical PageRank provides a valuable tool for understanding and predicting movement flows within spatial networks. Initially developed for web ranking, its adaptability to geospatial contexts has been proven in applications ranging from urban mobility to optimizing facility location (Chin & Wen, 2015; Yi et al., 2022). By integrating factors such as spatial proximity, connectivity, and the attractiveness of destinations, Geographical PageRank offers a context-aware approach to modeling movement tendencies. Jiang & Jia (2009) specifically used PageRank, and its variant weighted PageRank (WPR) and found out that the WPR specifically performs well in predicting aggregate flow of pedestrians in node based graphs. They specifically address the importance and usefulness of using agent-based simulation to capture complex movement in geographic space, and how WPR could be used to capture the aggregate flow in comparison to traditional methods.

The representation of spaces as networks underpins the application of graph-based algorithms like Geographical PageRank. Network theory concepts shed light on the relationships between spaces, connectivity, and the emergence of movement patterns (Borgatti & Lopez-Kidwell, 2014). The Role of Building Management Practices Campus management practices are increasingly influenced by the availability of smart building solutions. Studies emphasize that cost-effectiveness and a preference for utilizing existing infrastructure are key drivers for decision-making (Sutjarittham et al., 2018; Valks et al., 2021). Moreover, the capacity to monitor and optimize flexible space usage is essential for universities to better allocate resources and improve the campus experience.

1.2 Framework

This research employs a conceptual framework that integrates agent-based simulation (ABS) with spatial and temporal analysis to model indoor movement patterns in campus environments. The framework addresses the challenges of privacy-conscious indoor movement analysis, drawing upon key concepts from existing literature while adapting them to this specific context.

The framework is composed of interconnected components:

1. Agent Ontology: Inspired by Raubal (2001) and Bhattacharya et al. (2013), this component defines agent behavior, outlining factors influencing movement patterns. It allows for the simulation of spatial movements, classifiable into recognizable patterns through paths and stationary moments in space and time.

2. Modified PageRank Algorithm: This adapts the traditional PageRank algorithm to model room attractiveness in a spatial context, capturing the importance of spatial relationships in movement patterns.

3. Spatial Data Integration: This includes building layout, room types, and aggregated WiFi-based occupancy data, providing contextual information for realistic simulation while maintaining privacy.

4. Agent-Based Simulation Model: The core of the framework, implementing the agent ontology, modified PageRank algorithm, and spatial data to simulate indoor movement patterns.

5. Results and Insights Generation: The output of the simulation model, providing patterns and trends in indoor movement.

The framework emphasizes privacy preservation by using aggregated data and simulated agents, addressing concerns about data privacy in smart building solutions (Ahmad et al., 2021; Sun et al., 2021). It incorporates a dynamic feedback mechanism, continuously improving the model based on generated data.

Drawing from the OBiDE (Arslan et al., 2019) approach, the framework integrates contextual information such as room capacities, types, and building schedules into the agent ontology. This enables the simulation of agent movements based on environmental attributes, enhancing the framework's ability to predict and optimize indoor traffic flows.

The framework adopts the movement analysis taxonomy proposed by Andrienko et al. (2011), which categorizes movement analysis tasks into elementary and synoptic types. Elementary tasks in this model focus on individual agents and their specific movements, while synoptic tasks address collective patterns and trends. This approach allows us to analyze movement at multiple levels, from individual agent decisions to overall building usage patterns. By incorporating this taxonomy, we ensure a comprehensive analysis that addresses both micro-level agent behaviors and macro-level movement dynamics

Agents are conceptualized as spatio-temporal objects, representing people moving through space and time. The framework uses a time-based approach to data collection, capturing agent positions and actions at each simulation step. This granular data is aggregated to analyze flow patterns inside the building, utilizing flow maps based on the graph edges on which agents move.

The framework's strength lies in its ability to combine agent behavior understanding, ontological modeling, and movement behavior analysis to provide macro-level insights. It prioritizes the emergence of larger patterns and trends over individual agent movements. Environmental factors and spatio-temporal components contribute to determining location attractiveness, which in turn influences agent behavior, creating a dynamic feedback loop.

The accuracy of the agent ontology is fundamental to this feedback loop. By carefully defining and refining this ontology, the simulation aims to produce realistic and insightful results about indoor movement patterns in campus environments.

This framework provides an approach which is flexible while attempting to focus on the research questions. It bridges the gap between the need for detailed movement data and the imperative to protect individual privacy.

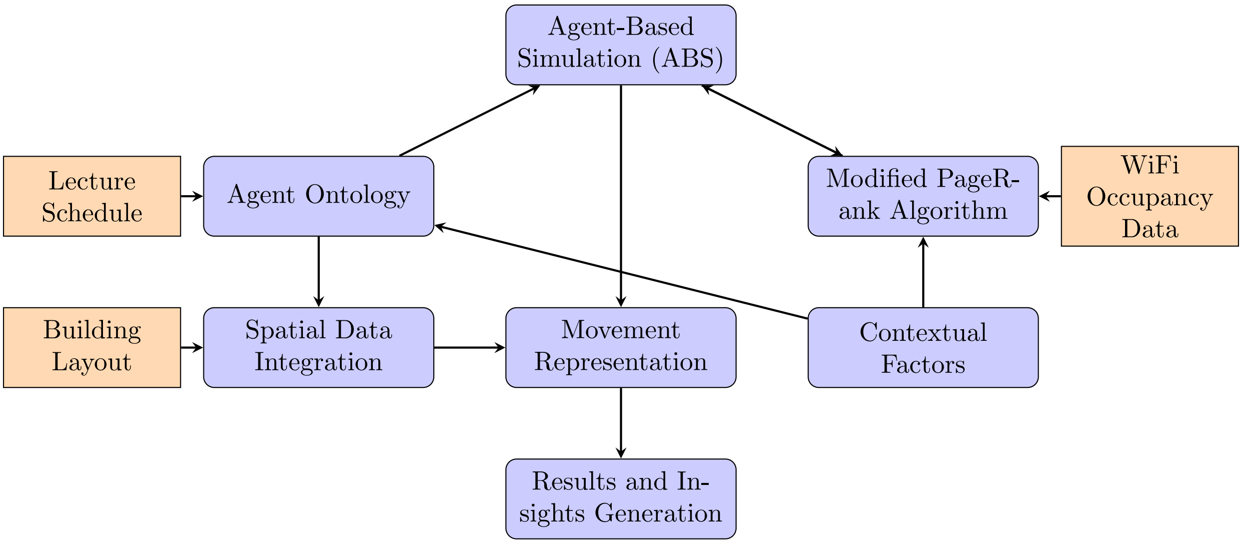

Figure 1. Conceptual model

2 Method

The Agent-Based Simulation (ABS) model implements a sophisticated approach to simulating indoor movement patterns within a complex building environment. The model incorporates multiple interacting components, including dynamic room attractiveness, geographical influences, agent decision-making processes, and social dynamics. These components work together to produce realistic movement behaviours that can be validated against real-world data. The model is created using the Mesa library (Kazil et al., 2020) in Python, utilizing a graph created using NetworkX for movement and representing the spatial environment. The elements of the model are desrcibed in Figure 3.

2.1 Research area

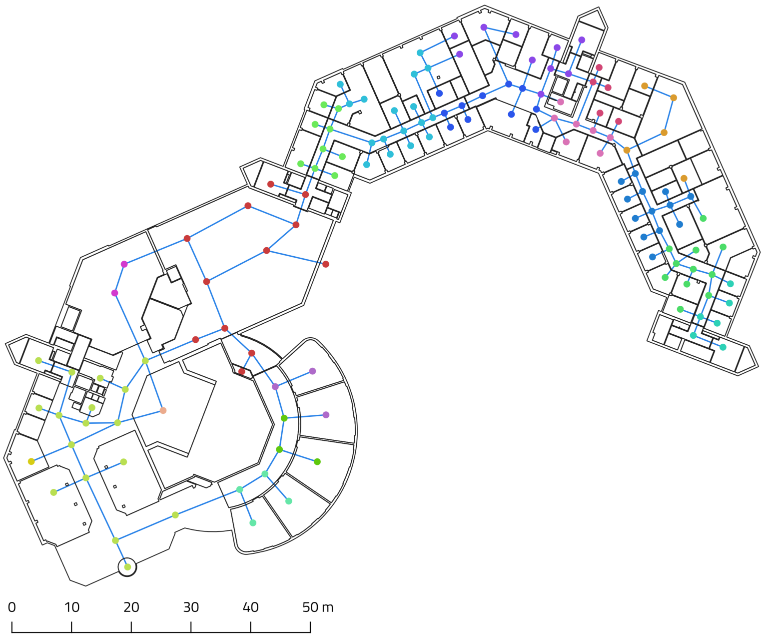

Figure 2. Research area building and areas with access points by color

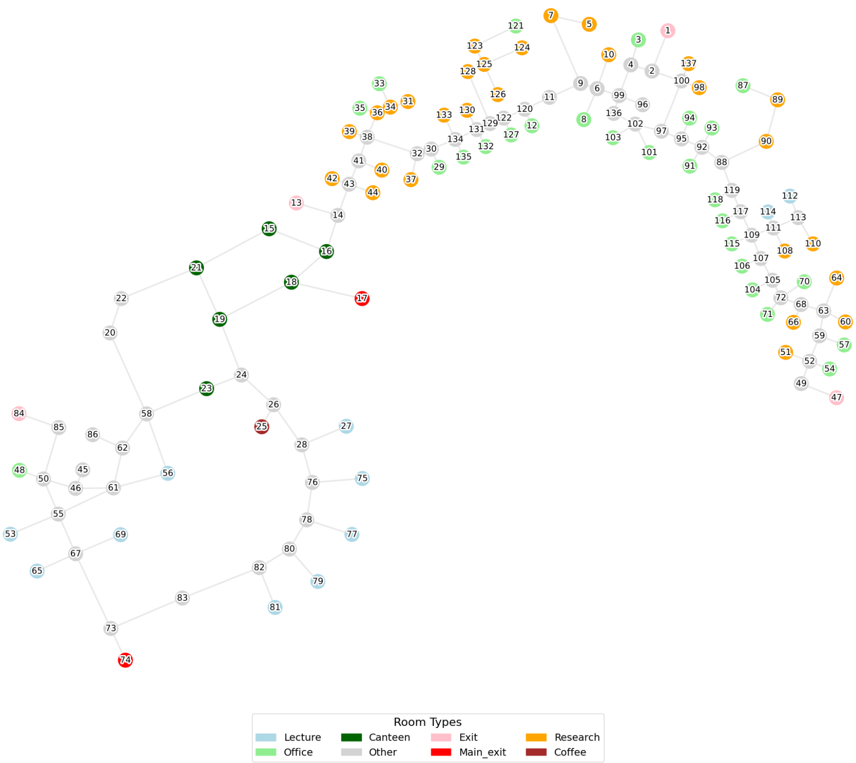

Figure 3. Research area building and areas with access points by color

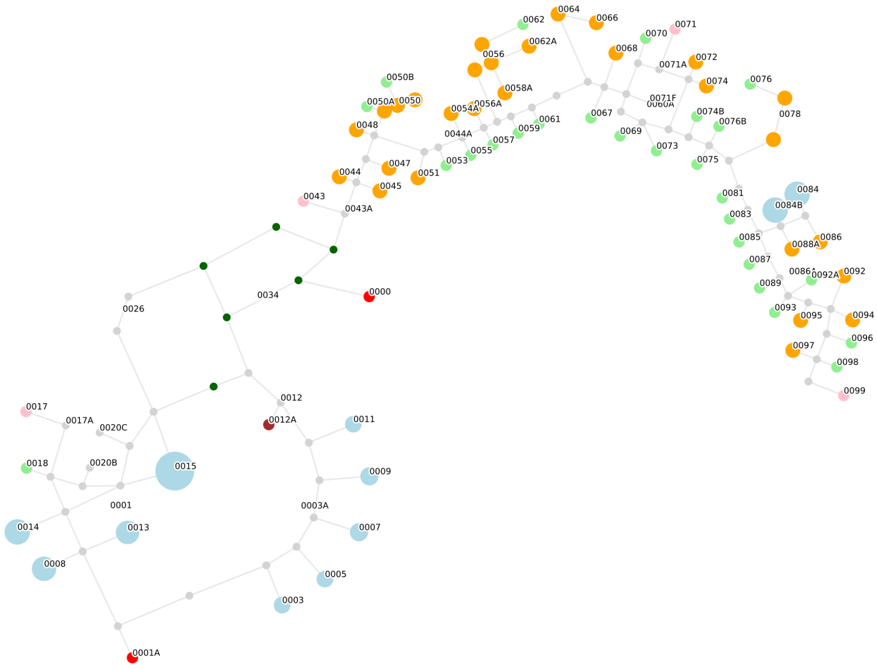

Figure 4. Room numbers and capacity based on node size

The focus of this research is on a campus environment, and specifically I am focusing on a building belonging to the University of Groningen. The specific building is seen in Figures 2, 3 and 4, and includes a variety of different uses for space. This is the main reason for selecting this specific building, as it has lecture rooms, offices, labs, a canteen and other spaces with a clear structure. Additionally, for the purposes of limiting the research scope, only the ground floor of the building is selected, and staircases will be considered as exits. In total, there are 11 lecture rooms, 25 offices, 27 research spaces and one canteen. There are 2 actual entrances/exits, and 4 staircases in the building. The other types are considered as unknown. The rooms are represented as nodes for the simulation, and as seen in Figure 3, some spaces, especially canteen and research labs will have the room split into multiple nodes. In addition, the building is divided into areas based on the locations of WiFi access points and their assumed areas of connectivity represented by colors in Figure 2, which will be important for validation purposes.

2.2 Data

The data used for the simulation and this research is for a period between 2023-02-10 and 2023-05-10. The data was acquired from a database stored at the University of Groningen. The sources of data include the building layout and room types, which were modified into a graph structure. Aggregated WiFi access point device counts were extracted from the database, and transformed to represent either building occupancy, or occupancy per area in the building. The client count value was divided by 1.5 to have a closer representation of actual people counts, based on validation conducted by Niemi & van der Meulen (2023) for this specific WiFi dataset. Additionally, lecture schedules were acquired from the schedules provided publicly by the University of Groningen, with location, start and end times and a planned size for the lectures. All in all, the usage of these datasets allows us to do simulation and validation of the model.

2.3 Model structure

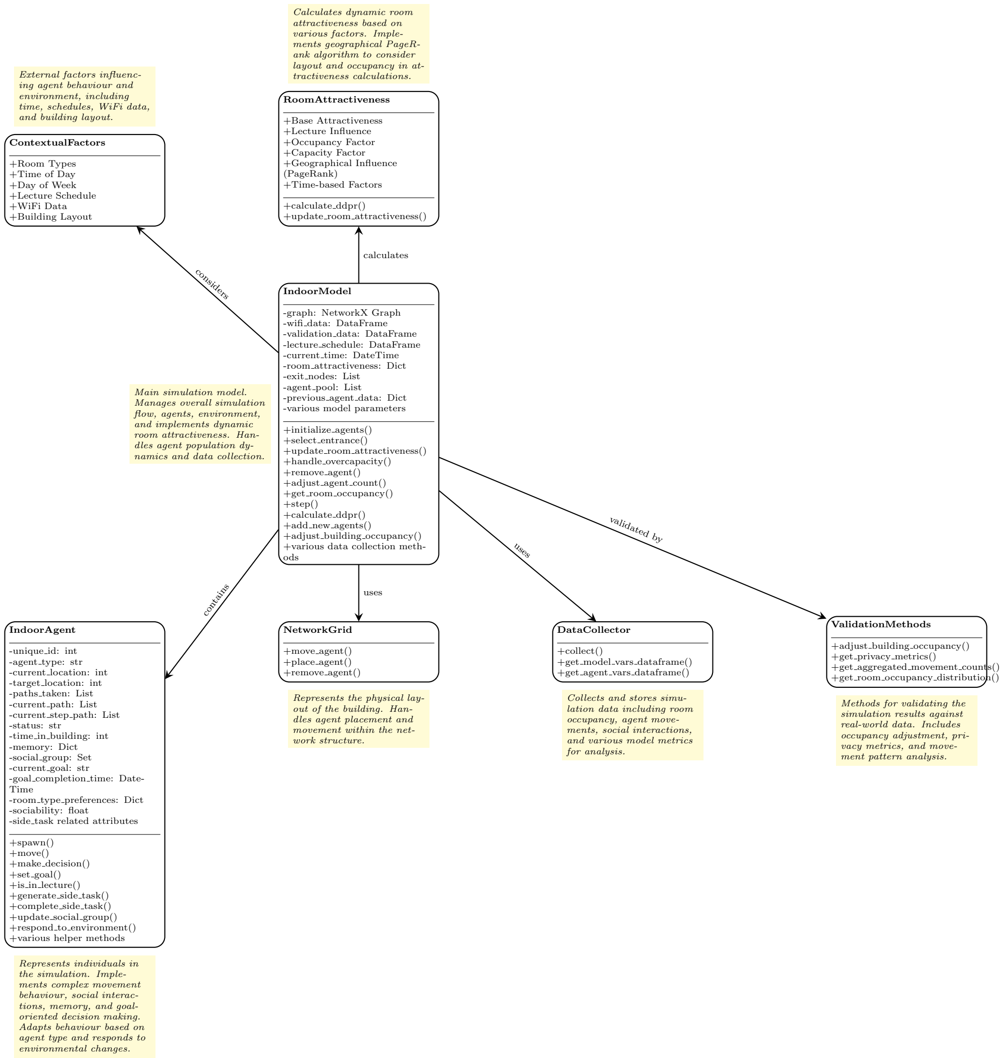

Figure 5. Representation of the ABS model architecture

The core of the simulation is the IndoorModel class, which orchestrates the entire simulation process. This class manages the simulation environment, agents, and data collection. It initializes with several key components, including a NetworkX Graph representing the building layout, WiFi data for model validation, a lecture schedule, and various tunable parameters that influence agent behaviour and room attractiveness. The IndoorModel class is responsible for several critical functions, including initializing and managing agents, updating room attractiveness, handling building occupancy and overcapacity situations, coordinating the simulation steps, and collecting and processing simulation data.

One of the key features of the IndoorModel is its ability to dynamically adjust the agent population to match real-world occupancy data. This is achieved through the `adjust_building_occupancy()` method, which compares the current simulation occupancy with target occupancy data and signals agents to enter or leave the building as necessary. This dynamic adjustment ensures that the simulation maintains a realistic representation of building occupancy throughout the simulated time period.

2.4 Room attractiveness

The main component of the model is the calculation of room attractiveness, which significantly influences agent movement decisions. This research consider attractiveness on two levels: a base calculation incorporating various environmental factors, and a more complex calculation using Distance-Decay PageRank (DDPR) to account for spatial relationships within the building. The base attractiveness of a room, denoted by $A(r, t)$, is calculated as a function of several factors:

$$A(r,t) = B(r) \cdot L(r,t) \cdot C(r,t) \cdot T(r,t) \cdot D(r) \cdot (1 + PR(r))$$

$$\begin{aligned}
&\text{Where:}\\
A(r,t) &: \text{Attractiveness of room } r \text{ at time } t\\
B(r) &: \text{Base attractiveness of room } r\\
L(r,t) &: \text{Lecture influence factor}\\
C(r,t) &: \text{Capacity factor}\\
T(r,t) &: \text{Time-based factor}\\
D(r) &: \text{Room type factor}\\
PR(r) &: \text{PageRank score of room } r
\end{aligned} \tag{1}$$

Each of these factors captures a different aspect of room attractiveness. The lecture influence factor $L(r,t)$ increases the attractiveness of rooms with ongoing or upcoming lectures, considering the time until the lecture starts and the planned lecture size. The capacity factor $C(r,t)$ decreases attractiveness as a room approaches its maximum capacity, preventing overcrowding. The time-based factor $T(r,t)$ accounts for temporal variations, such as increased canteen attractiveness during lunch hours. The room type factor $D(r)$ allows for differentiation based on room function, e.g., reducing the attractiveness of hallways and rooms with unknown types. These factors are defined as follows:

$$\begin{aligned}
L(r,t) &= \begin{cases} 1 + \alpha \cdot (5 - \Delta t/30) \cdot S, & \text{if upcoming lecture}\\ 1 + \beta \cdot (P - O(r,t))/P \cdot S, & \text{if ongoing lecture}\\ 1, & \text{otherwise} \end{cases}\\
C(r,t) &= \begin{cases} 1 - O(r,t)/M(r), & \text{if } O(r,t) < M(r)\\ 0, & \text{if } O(r,t) \geq M(r) \end{cases}\\
T(r,t) &= \begin{cases} 5, & \text{if } r \text{ is canteen and } 11 \leq t_{hour} \leq 14\\ 1, & \text{otherwise} \end{cases}\\
D(r) &= \begin{cases} 0.0001, & \text{if } r \text{ is 'other' (e.g., hallway)}\\ 1.5, & \text{if } r \text{ is office}\\ \lambda, & \text{if } r \text{ is lecture room}\\ 1, & \text{otherwise} \end{cases}
\end{aligned} \tag{2}$$

In the formula above, Δt is the time until lecture starts (in minutes), P is the planned size of the lecture, $O(r,t)$ is the current occupancy of room r at time t, $M(r)$ is the maximum capacity of room r, S is the size factor $(P/100)^{\text{lecture\_size\_influence}}$, and α, β, λ are contextual factors that can be tuned as parameters.

To incorporate the spatial relationships between rooms, I implement a modified version of the PageRank algorithm, namely an extended version Distance-Decay PageRank (DDPR) used in Chin & Wen (2015). This algorithm calculates a score $PR(R_i)$ for each room R_i based on its connections to other rooms and their occupancy:

$$PR(R_i) = (1 - d) + d \sum_{j \in K(R_i)} \frac{W_{ji}}{\sum_{k \in K(R_j)} W_{jk}} PR(R_j) \cdot (1 + O(R_j,t)/M_{max}) \tag{3}$$

Where d is a damping factor (which is typically set at 0.85), $K(R_i)$ is the set of k nearest neighbors of R_i, W_{ji} is the weight of the edge between rooms R_j and R_i (calculated as $1/dist(R_j, R_i)^f$, where f is a tunable distance factor), $O(R_j,t)$ is the current occupancy of room R_j, and M_{max} is the maximum occupancy across all rooms. This DDPR score is then incorporated into the overall attractiveness calculation, allowing rooms to influence each other's attractiveness based on their spatial relationships and current occupancy levels.

2.5 Agent decision making

Agents in the model make movement decisions based on the attractiveness of available rooms and several other factors. The probability of an agent a choosing a room r at time t is given by:

$$P(r|a,t) = \frac{w(r,a,t)}{\sum_{r' \in V(a)} w(r',a,t)} \tag{4}$$

Where: $w(r,a,t)$ is the weight of room r for agent a at time t, and $V(a)$ is the set of valid target rooms for agent a. The weight calculation incorporates various factors:

$$w(r,a,t) = A(r,t) \cdot M(r,a) \cdot S(r,a) \cdot D(r,a) \cdot H(r) \cdot F(r,a) \cdot R(r,a) \tag{5}$$

These factors include a memory factor $M(r,a) = 1 + m \cdot visits(r,a)$ reflecting the agent's familiarity with the room, a social factor $S(r,a) = 1 + s \cdot |SG(a) \cap O(r,t)|$ considering the presence of the agent's social connections in the room, a distance decay factor $D(r,a) = 1/(1 + \delta \cdot \max(0, dist(a,r) - 10))$ reducing the attractiveness of faraway rooms, a hallway avoidance factor $H(r)$, and factors $F(r,a)$ and $R(r,a)$ for student agents to avoid office and research areas. Here, m, s, and δ are tunable parameters, $visits(r,a)$ is the number of times agent a has visited room r, $SG(a)$ is the social group of agent a, $O(r,t)$ is the set of agents occupying room r at time t, and $dist(a,r)$ is the distance between agent a's current location and room r.

The model also incorporates time-dependent movement probabilities and social dynamics. The probability of an agent moving at a given time is defined as:

$$P(\text{move}|a,t) = \begin{cases} p_b, & \text{if } 8 \leq t_{hour} < 18 \\ p_a, & \text{otherwise} \end{cases} \tag{6}$$

Where p_b is the base movement probability during working hours and p_a is the after-hours movement probability. Social connections between agents are formed based on their sociability factors:

$$P(\text{social connection}|a_1, a_2) = s_{a_1} \cdot s_{a_2} \tag{7}$$

Where s_{a_1} and s_{a_2} are the sociability factors of agents a_1 and a_2 respectively.

This ABS model provides a flexible and comprehensive framework for simulating indoor movement patterns. By incorporating dynamic room attractiveness, spatial relationships, individual agent decision-making, and social dynamics, this research aims to capture the complexity of human movement within built environments accurately, while using relatively simple agent ontology and model control. The model includes numerous tunable parameters that can be adjusted to align simulation results with real-world data. These parameters influence room attractiveness, agent movement probabilities, and social interaction rates. The process employs a systematic calibration process, comparing simulated occupancy patterns and movement flows against WiFi-based location data and to ensure the model's validity, and to tune parameters to work as well as possible, improving the capability in representing real-world scenarios.

2.6 Agent representation and behaviour

The IndoorAgent class represents individuals within the simulation. Each agent is characterized by a comprehensive set of attributes that define its state and behaviour within the simulated environment. These attributes include a unique identifier, agent type (student or employee), current and target locations, movement history (paths taken), current status (e.g., moving, idle), time spent in the building and current location, memory of visited locations, social group, current goal and goal completion time, room type preferences, and a sociability factor.

Agents make decisions and move within the simulated environment based on a complex set of rules and probabilities. The IndoorAgent class implements several key methods to govern agent behaviour. The `spawn()` method initializes the agent at an entrance node, setting its initial state and preparing it for interaction with the environment. The `move()` method handles the agent's movement between rooms, considering factors such as distance, room attractiveness, and the agent's current goal. The `make_decision()` method is crucial in determining the agent's next action, taking into account various environmental and personal factors. The agent ontology aligns with the object-focused analysis in the Andrienko et al. (2011) taxonomy. Each agent, representing a mover in the framework, is characterized by its spatio-temporal position (current location and time) and various attributes (agent type, goals, social connections). The agent's decision-making processes, including the `make_decision()` and `set_goal()` methods, correspond to the elemental tasks in the taxonomy, focusing on individual object behaviors. Meanwhile, the collective behavior emerging from these individual decisions aligns with the synoptic tasks, allowing us to analyze overall movement patterns and space utilization.

The `set_goal()` method assigns a new goal to the agent, which could be attending a lecture, studying, or engaging in social activities. This goal-setting mechanism allows for the simulation of purposeful movement within the building. The `update_social_group()` method manages the agent's social connections, simulating the formation and evolution of social networks within the simulated population. The `respond_to_environment()` method allows agents to adjust their behaviour based on changing environmental conditions, such as room occupancy or time of day.

The agent decision-making process, as previously described, considers room attractiveness, social factors, memory, and various environmental conditions. Additionally, agents can generate and complete side tasks, simulating realistic behaviour patterns such as getting coffee or engaging in quick study sessions. This complex interplay of factors and behaviours allows for a nuanced and realistic representation of individual movement patterns within the simulated environment.

2.7 Spatial representation

The spatial structure of the building is represented using a NetworkGrid, which is built upon the NetworkX Graph. This grid system allows for efficient agent movement and spatial calculations. Each node in the graph represents a room or area within the building, with edges representing connections between these spaces. This representation captures the physical layout of the building, including the relationships between different areas and the possible paths agents can take.

The NetworkGrid provides essential methods for managing agent positions within the simulated space. The `move_agent()` method relocates an agent from one node to another, simulating movement through the building. This method ensures that agent movements are constrained by the physical layout of the building, allowing only valid transitions between connected spaces. The `place_agent()` method positions an agent at a specific node, which is particularly useful during agent initialization or when simulating entry into the building. The `remove_agent()` method removes an agent from the grid, simulating exit from the building or the end of an agent's participation in the simulation.

These methods are crucial for maintaining the spatial integrity of the simulation and ensuring that agent movements align with the physical layout of the building. By using a graph-based representation, the model can efficiently calculate distances between locations, identify neighboring spaces, and determine valid movement paths, all of which are essential for realistic agent behaviour and movement patterns.

2.8 Contextual factors

The model incorporates various contextual factors that influence agent behaviour and room attractiveness, creating a dynamic and realistic simulation environment. Room types play a significant role, with different types such as lecture rooms, offices, and study areas having distinct base attractiveness values and influencing agent behaviour differently. For instance, lecture rooms may have higher attractiveness for students during scheduled lecture times, while offices may be more attractive to employee agents during working hours.

The model considers time-dependent factors, recognizing that the attractiveness and usage of spaces can vary significantly throughout the day. For example, the attractiveness of the canteen increases during lunch hours, simulating the natural flow of people during meal times. Similarly, the model implements different movement probabilities for agents during working hours and after hours, reflecting the changing dynamics of building usage over time.

While not explicitly mentioned in the provided code, the model structure allows for the incorporation of day-specific behaviours, which could be used to simulate differences between weekdays and weekends or specific day-of-week patterns. The lecture schedule is a crucial contextual factor, significantly influencing room attractiveness and agent movement, particularly for student agents. Ongoing and upcoming lectures increase the attractiveness of lecture rooms, simulating the gathering of students for classes.

WiFi data serves a dual purpose in the model, being used both for model validation and to guide the adjustment of building occupancy. This data provides a real-world benchmark against which the simulation results can be compared and adjusted. The physical structure of the building, represented by the NetworkX Graph, plays a crucial role in determining movement patterns and room accessibility. It defines the possible paths agents can take and influences the calculation of room attractiveness through factors such as proximity and connectivity.

These contextual factors are deeply integrated into various components of the model, including room attractiveness calculations, agent decision-making processes, and overall simulation dynamics. By considering these factors, the model can replicate the complex and dynamic nature of human movement within built environments, responding to changing conditions and schedules throughout the simulated period.

2.9 Data collection and analysis

The DataCollector class is an important part of the simulation model, responsible for gathering and storing a wide range of simulation data for subsequent analysis. At each time step, it collects various metrics that provide insights into the state and dynamics of the simulated environment. These metrics include room occupancy, which tracks the number of agents in each room over time, and total building occupancy, offering an overview of the building's usage patterns. The collector also records room attractiveness values and modified PageRank scores, allowing for analysis of how these factors influence agent behaviour and movement patterns.

To understand agent behaviour on both individual and aggregate levels, the DataCollector tracks the average distance traveled by agents, providing insights into mobility patterns within the building. It also maintains data on agent type distribution, allowing for analysis of how different agent types (e.g., students vs. employees) utilize the space. Social group sizes are recorded to study the formation and evolution of social dynamics within the simulated population.The collected data is aligned with both the elementary and synoptic task types outlined in the Andrienko et al. (2011) taxonomy. At each time step, it collects metrics that provide insights into the state and dynamics of the simulated environment, capturing both individual agent behaviors (elementary level) and overall patterns (synoptic level).

The model implements several sophisticated methods for analyzing the collected data, each offering unique insights into different aspects of the simulation. The `get_average_distance_traveled()` method calculates the mean distance covered by all agents, offering a measure of overall mobility within the simulated environment. The `get_agent_type_distribution()` method provides a breakdown of agent types present in the simulation at any given time, allowing for analysis of how different user groups occupy and move through the space.

Social dynamics are examined through the `get_social_group_sizes()` method, which analyzes the size distribution of social groups formed during the simulation. This can offer insights into social behaviour patterns and their impact on movement and space utilization. The `get_room_type_preference_distribution()` method examines how different agent types prefer various room types, potentially revealing patterns in space usage and informing building design or management strategies.

The `get_room_occupancy_distribution()` method offers a detailed examination of how occupancy is distributed across different rooms and areas of the building. This can reveal hotspots of activity, underutilized spaces, and how occupancy patterns change over time.

These data collection and analysis methods provide a toolset for understanding the simulation's behaviour. They allow for detailed examination of various aspects of the simulated environment and agent behaviour, from individual movement patterns to building-wide trends. Moreover, these methods facilitate comparison with real-world data, serving as a crucial component in the validation and refinement of the simulation model.

2.10 Model validation

Validation of the model is performed through an approach composed of many steps, ensuring that the simulation accurately represents real-world indoor movement patterns. A primary validation method involves comparison with WiFi data. The model continuously adjusts building occupancy based on real WiFi data, ensuring that the simulated population closely matches observed patterns. This dynamic adjustment allows the model to replicate daily and weekly fluctuations in building usage, providing a realistic representation of occupancy over time.

Occupancy distribution analysis forms another crucial part of the validation process. The simulated room occupancy distribution is meticulously compared against real-world observations. This comparison verifies the model's accuracy in predicting space utilization across different areas of the building. It helps identify any discrepancies between simulated and observed usage patterns, allowing for fine-tuning of the model parameters to improve accuracy.

Movement pattern analysis provides insights into the dynamic aspects of the simulation. Aggregated movement counts from the simulation are compared with expected patterns based on building layout and known usage patterns. This analysis helps verify that the simulated agents are moving through the building in ways that align with real-world behaviour, considering factors such as common paths, bottlenecks, and time-dependent movement trends.

The model also computes privacy metrics as part of its validation process. These metrics ensure that while the simulation provides detailed insights into movement patterns and space usage, it does so in a way that respects privacy constraints. This is particularly important when the model is used in contexts where individual privacy must be maintained, such as in workplace or educational settings.

The `adjust_building_occupancy()` method plays a pivotal role in the ongoing validation process. By dynamically adjusting the agent population to match target occupancy data derived from real-world observations, this method ensures that the simulation remains aligned with actual building usage throughout the simulated period. This continuous adjustment allows the model to adapt to unexpected changes or anomalies in building usage, maintaining its accuracy over extended simulation runs.

Through this comprehensive validation approach, combining data comparison, distribution analysis, movement pattern verification, and privacy considerations, it is ensured that the ABS model provides a reliable and accurate representation of indoor movement patterns. This rigorous validation process not only verifies the model's accuracy but also provides valuable insights for iterative improvement of the simulation framework.

2.11 Simulation process

The simulation progresses through discrete time steps, each representing a specific point in time. One step approximates to around 3 real world minutes. At each step, a series of processes occur in a sequence to update the state of the simulated environment and its agents. First, the current time is updated, moving the simulation forward. This temporal progression is done to enable for time-dependent behaviours and for aligning the simulation with real-world data used for validation.

Following the time update, room attractiveness is recalculated based on the current state of the environment. This recalculation takes into account various factors such as ongoing or upcoming lectures, current occupancy levels, time of day, and other contextual factors. The dynamic nature of room attractiveness is key to simulating realistic movement patterns, as it influences agents' decision-making processes.

Next, building occupancy is adjusted to match validation data. This step involves comparing the current simulated occupancy with target occupancy derived from real-world data, such as WiFi logs. Based on this comparison, the model may signal for agents to enter or leave the building, ensuring that the simulated population closely mirrors real-world occupancy patterns.

Agents are then added or removed as necessary, based on the occupancy adjustment. New agents may be spawned at entrance points, while others may be directed to exit the building. This dynamic population management allows the simulation to maintain realistic occupancy levels throughout the simulated period.

With the environment updated, each agent in the simulation performs its step function. This function may involve various actions such as moving to a new location, making decisions about future actions, updating the agent's state, or interacting with other agents or the environment. The specific actions taken by each agent depend on its current state, goals, and the surrounding environmental conditions.

Finally, data is collected for the current time step. This data collection process captures a snapshot of the simulation state, including agent positions, room occupancies, movement patterns, and other relevant metrics. This collected data is crucial for later analysis and validation of the simulation results.

This process continues for a specified number of time steps or until a termination condition is met. The iterative nature of the simulation allows for the emergence of complex patterns and behaviours over time, providing insights into how indoor spaces are utilized and how individuals move within built environments.

In conclusion, the ABS model provides a comprehensive framework for simulating indoor movement patterns. By incorporating dynamic room attractiveness, spatial relationships, individual agent decision-making, social dynamics, and various contextual factors, I aim to capture the complexity of human movement within built environments accurately. The model's flexibility, coupled with its data collection and validation mechanisms, allows for fine-tuning and adaptation to specific scenarios, making it a valuable tool for understanding and predicting indoor movement patterns in complex building environments.

The results for the simulation are presented through a descriptive analysis, using series of validated metrics, visualizations, and simple statistical analyses, providing an examination of the model's performance and insights collected from the simulation.

2.12 Ethical statement

During this research, no data identifying individuals is used. Albeit I am one of the managers for the data used in this study, I have confirmed with a second data manager that the data used cannot be used to identify people. This concerns the data from the WiFi access points as well, where at no point personally identifiable information is accessed, and data is only available in aggregate counts of connected devices per access point. Additionally, I need to address the deterministic and positivist nature of this research and how it might not consider movement patterns for individuals with mobility restrictions, or other movement patterns related to accessibility, and when interpreting the results this needs to be taken into account.

In this research, the following AI tools have been used for different purposes. When writing code for the model, Github Copilot has been active and I have used code completions for boilerplate code. For assisting in writing mathematical equations in LaTeX, I have used Claude Sonnet 3.5 (2024-06-20) model from Anthropic AI, using natural language descriptions to have the LLM aid in writiting the mathematical equations. Additionally, I have used Grammarly to restructure paragraphs and to help me write in a more clear and academic manner to communicate my message better.

3 Results

3.1 Overview

This section presents a comprehensive analysis of the findings from the Agent-Based Simulation (ABS) model, addressing the main research question on modeling indoor movement patterns in campus environments while ensuring individual privacy. I explore in detail the subquestions related to room attractiveness modeling, agent ontology, and the role of spatial factors in indoor behaviour.

3.2 Model validation

The validity of the ABS model was rigorously assessed through comparison with real-world WiFi data, ensuring that the simulated occupancy patterns closely match observed behaviour in the campus environment. This validation process is one of the main methods for establishing the reliability and accuracy of the privacy-conscious methodology.

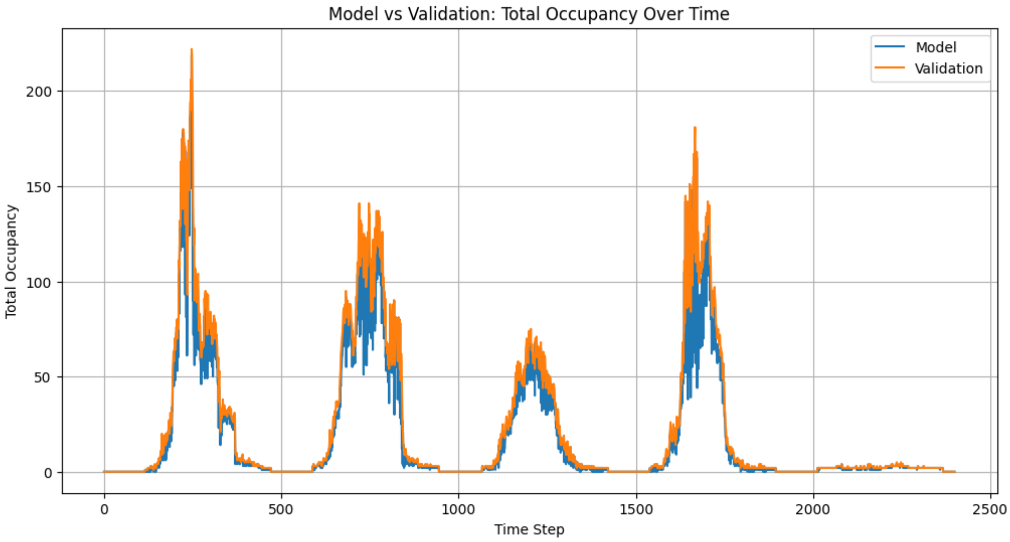

Figure 6. Total occupancy validation

Figure 6 illustrates the total occupancy validation, demonstrating a strong correlation between simulated and actual building occupancy over time. The graph reveals that the model successfully captures the overall trends in building usage, including peak periods and low points in activity. The close alignment between the simulated and observed occupancy curves suggests that the model effectively replicates the macro-level dynamics of building utilization. However, it's important to note that while the general trends are well-captured, there are some discrepancies, particularly during peak hours. These differences might be attributed to factors not fully accounted for in the model, such as unexpected events or external influences on building occupancy that are not reflected in the WiFi data. It also has to be noted, that the model does adjust the agent count based on the total occupancy of the building. While not modelled to follow it 1-to-1 due to aggressive agent removal and addition if that is done, this data by default should be expected to follow the actual values closely.

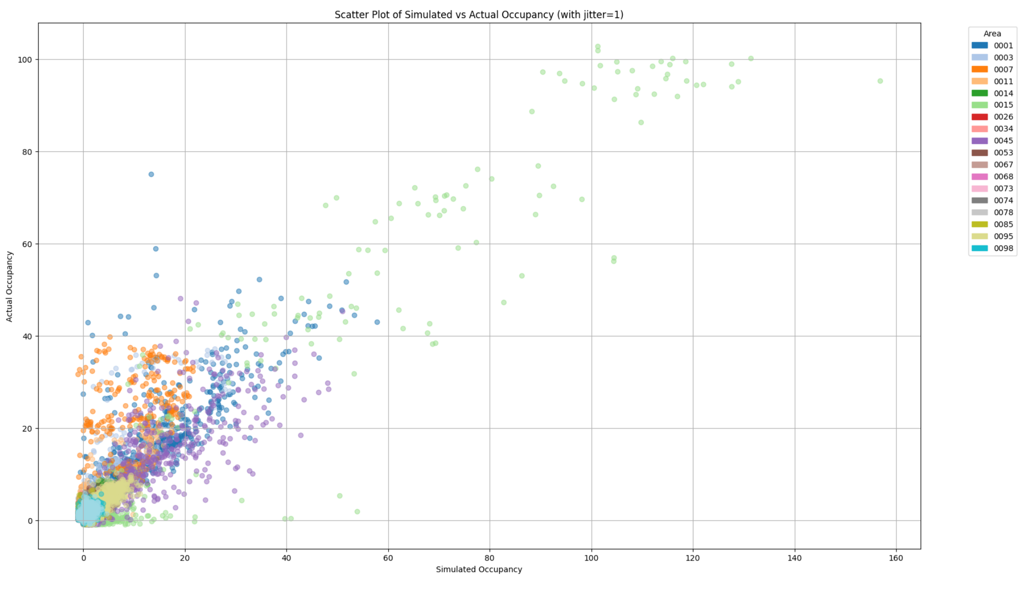

Figure 7. Simulated occupancy vs validation occupancy per area

For a more granular analysis, Figure 7 provides a detailed comparison of simulated occupancy against validation data for individual areas within the building. This area-specific validation is crucial for understanding how well the model performs across different spaces with varying functions and characteristics. The plot in Figure 7 reveal different degrees of accuracy across different areas. Some areas, such as 0015 and 0001, show excellent correlation between simulated and observed occupancy, with the model closely tracking both the magnitude and temporal patterns of space utilization. Other areas, like 0026 and 0045, exhibit more significant discrepancies, indicating potential areas for model improvement. Area 0015 is a large lecture room, and area 0001 is the main entrance area, so this is to be expected. On the other hand, area 0026 is a canteen area, and it is expected that with simple logic for lunch behaviour, this is not captured as well as other areas.

Area	RMSE	NRMSE	R^2
0007	5.02	0.1286	0.5684
0015	4.63	0.0453	0.8993
0001	3.94	0.0525	0.8123
0034	3.16	0.0645	0.7808
0003	2.55	0.0688	0.7245
0011	1.19	0.0626	0.7646
0014	0.80	0.0890	0.6616
0053	0.80	0.1139	0.7219
0073	0.78	0.1298	0.6109
0067	0.76	0.0763	0.7030
0078	0.73	0.1043	0.5236
0026	0.73	0.1454	-0.1859
0085	0.69	0.0686	0.9026
0098	0.58	0.1168	0.5177
0068	0.54	0.1080	0.2206
0074	0.48	0.1192	0.3711
0095	0.46	0.0926	0.5884
0045	0.42	0.1051	0.0943

Table 1. Areas Ranked by Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE), and R^2

To quantify the model's performance across different areas, Table 1 presents key statistical metrics: Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE), and R^2 values. These metrics provide a view of the model's accuracy and its ability to explain the variance in observed data. The results in Table 1 demonstrate that the majority of areas show good agreement between simulated and observed occupancy. Areas such as 0015, 0001, and 0034 exhibit high R^2 values (0.8993, 0.8123, and 0.7808 respectively), indicating that the model captures a significant portion of the variance in real-world data for these spaces. The low NRMSE values for these areas (0.0453, 0.0525, and 0.0645) further support the model's accuracy. Still, some areas show poorer performance. Notably, area 0026 has a negative R^2 value (-0.1859), suggesting that for this particular space, the model's predictions are worse than a horizontal line representing the mean of the observed data. This indicates a clear area for future model refinement, possibly requiring additional contextual factors or adjusted parameters specific to this space. The variation in model performance across different areas highlights the complexity of indoor movement patterns and the challenges in creating a one-size-fits-all model for diverse spaces within a building. While the model performs well for many areas, the discrepancies in others point to the need for further investigation into area-specific factors that may influence occupancy and movement patterns.

3.3 Room attractiveness

Addressing the first subquestion on modeling room attractiveness in a spatio-temporal context, I analyze the dynamics of room attractiveness as calculated by the modified PageRank algorithm and other conditional factors.

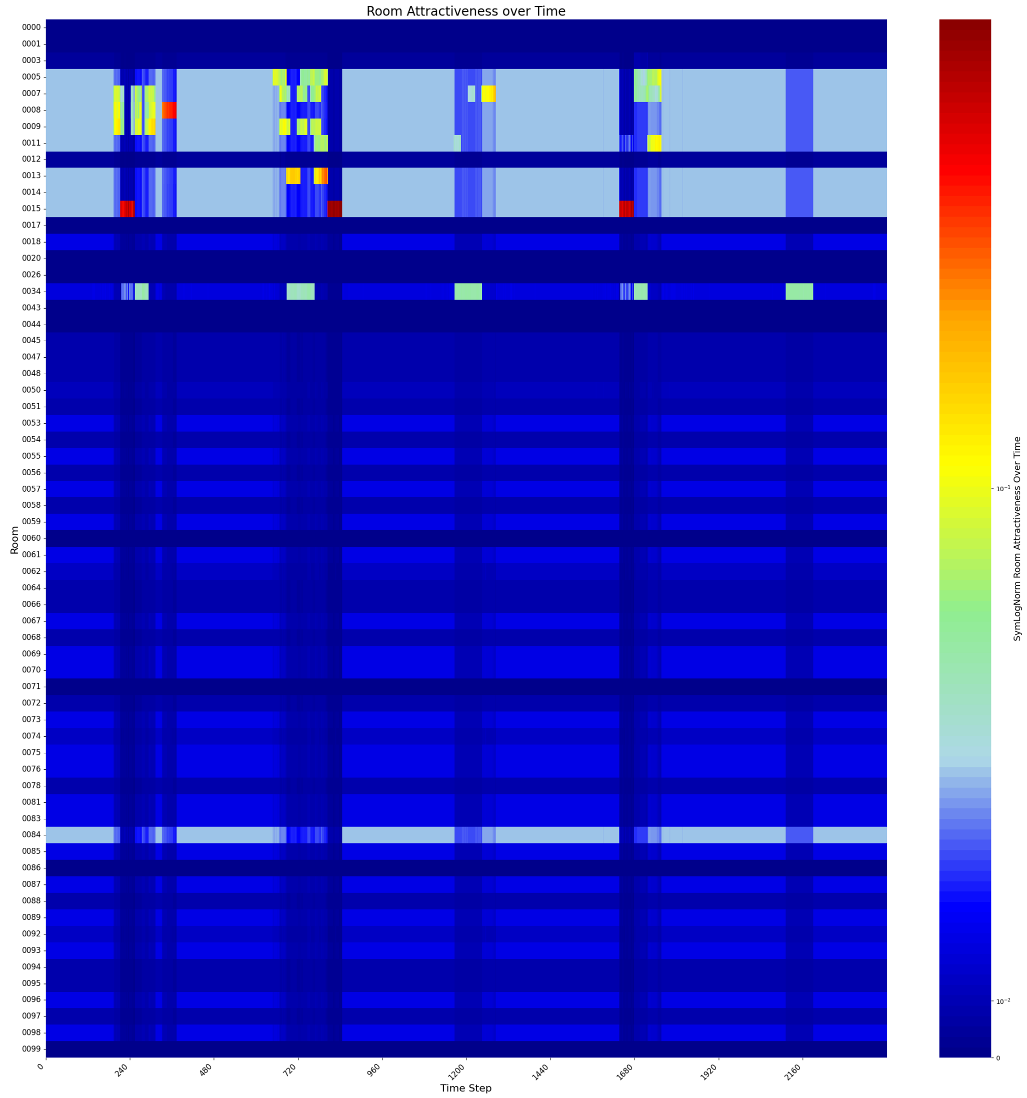

Figure 8. Room attractiveness over time

Figure 8 provides a visualization of room attractiveness over time for various spaces within the building. For reference, Figure 4 provides the locations of the rooms with their capacities. This graph shows how the model incorporates both spatial and temporal factors to determine the likelihood of agents moving to specific locations. The fluctuations in attractiveness values demonstrate the model's responsiveness to various factors such as scheduled events, current occupancy levels, and time of day. Notable peaks in attractiveness correspond to lecture times or other scheduled activities, reflecting the model's ability to capture the dynamic nature of space utilization in a campus environment. For instance, the sharp increases in attractiveness for rooms labeled as 'lecture' at regular intervals suggest the model's accurate representation of class schedules. The gradual rise and fall of attractiveness for these spaces also indicate the model's consideration of factors such as students arriving early or lingering after classes. The 'canteen' area shows low, which indicates that lunch behaviour is not captured well. All in all though, this demonstrates the model's capability to incorporate time-dependent behaviours that are crucial for realistic simulation of campus activities. Interestingly, areas labeled as 'office' show more stable attractiveness over time, with slight variations that might correspond to working hours. This stability aligns with the expected usage patterns of office spaces, which typically have more consistent occupancy during working hours. The 'research' areas exhibit a unique pattern, with periodic fluctuations that may represent the coming and going of researchers or the scheduling of experiments and meetings. This pattern highlights the model's ability to capture the distinct characteristics of different types of spaces within the campus environment. The varying patterns of attractiveness across different room types demonstrate the effectiveness of the modified PageRank algorithm in incorporating both the spatial relationships between rooms and the temporal aspects of building usage. This dynamic approach to room attractiveness is a key factor in simulating realistic movement patterns while maintaining individual privacy, as it allows the model to guide agent behaviour based on aggregated, time-varying metrics rather than individual-level data.

3.4 Parameter tuning

Parameter	Value
Study Area Leave Chance	0.02
Student Leave Chance	0.01
Social Influence	0.4
Social Group Size Min	2
Social Group Size Max	8
Social Group Probability	0.2
Research Leave Chance	0.06
Research Avoidance Factor	2.0
Other Area Leave Chance	0.6
Office Avoidance Factor	5.0
Movement Probability	0.17
Memory Influence	0.25
Lecture Size Influence	1.5
Lecture Leave Chance	0.01
Lecture Base Attractiveness	3.0
Exit Chance	0.007
Employee Ratio Variation	0.02
Employee Ratio	0.1
Distance Decay Factor	0.02
Coffee Leave Chance	0.7
Canteen Leave Chance	0.05
Base Movement Chance	0.012
After Hours Leave Chance	0.03

Table 2. Best parameter results from tuning

Table 2 presents these optimal parameter values, which provide information into the factors that most accurately simulate indoor movement patterns while preserving privacy. The tuning is done to minimise mean absolute error in the models predictions. The first 480 steps (20%) are used to tune the model. Several notable results are shown in this optimisation.

Social Influence (0.4): The relatively high optimal value for social influence contrasts with its low sensitivity in the sensitivity analysis. This suggests that while social factors may not dramatically alter overall patterns, they play a subtle but important role in fine-tuning agent behaviours to match observed patterns. Memory Influence (0.25): The moderate value for memory influence aligns with the sensitivity analysis, confirming the importance of past experiences in shaping agent decisions without dominating other factors. Distance Decay Factor (0.02): The low optimal value suggests that while distance is a consideration in movement decisions, it's less influential than other factors like room attractiveness or scheduled activities. Office and Research Avoidance Factors (5.0 and 2.0 respectively): These high values, particularly for office avoidance, indicate a strong tendency for non-employee agents to avoid these areas, reflecting realistic behaviour in a campus setting. Lecture Size Influence (1.5): The moderate value here, combined with its high sensitivity, underscores the balance in modeling lecture dynamics. It's strong enough to significantly influence movements but not so dominant as to overshadow other factors. Leave Chance Parameters: The generally low values for these parameters (e.g., Student Leave Chance at 0.01, Lecture Leave Chance at 0.01) suggest that agents tend to stay in their current locations once they arrive, with movements primarily driven by scheduled activities or specific goals rather than random departures. Social Group Parameters: The combination of low Social Group Probability (0.2) but wide size range (2-8) suggests that while social group formation is relatively infrequent, when groups do form, they can vary significantly in size. This captures the diversity of social interactions in a campus environment, from small study groups to larger social gatherings. Employee Ratio (0.1) and Employee Ratio Variation (0.02): These values indicate a relatively small but stable employee population in the simulation, reflecting the typical composition of a university building primarily occupied by students.

The optimized parameters reveal a model that tries to balance the influence of different factors on agent behaviour. It emphasizes the importance of scheduled activities (through lecture parameters) and space functionality (through avoidance factors) while still incorporating social and memory elements. The low leave chances across different space types suggest a model that prioritizes purposeful movements over random wandering, aligning with the goal-oriented nature of campus activities. However, it's important to note that these optimal values are specific to the particular campus environment and data set. While they work in this dataset to show the relative importance of different factors in shaping indoor movements, they should not be blindly applied to other settings without careful consideration and potential re-tuning.

3.5 Agent ontology

To address the second subquestion regarding the type of agent ontology best suited for guiding movement behaviour, I analyze the emergent patterns in agent movements and decision-making processes.

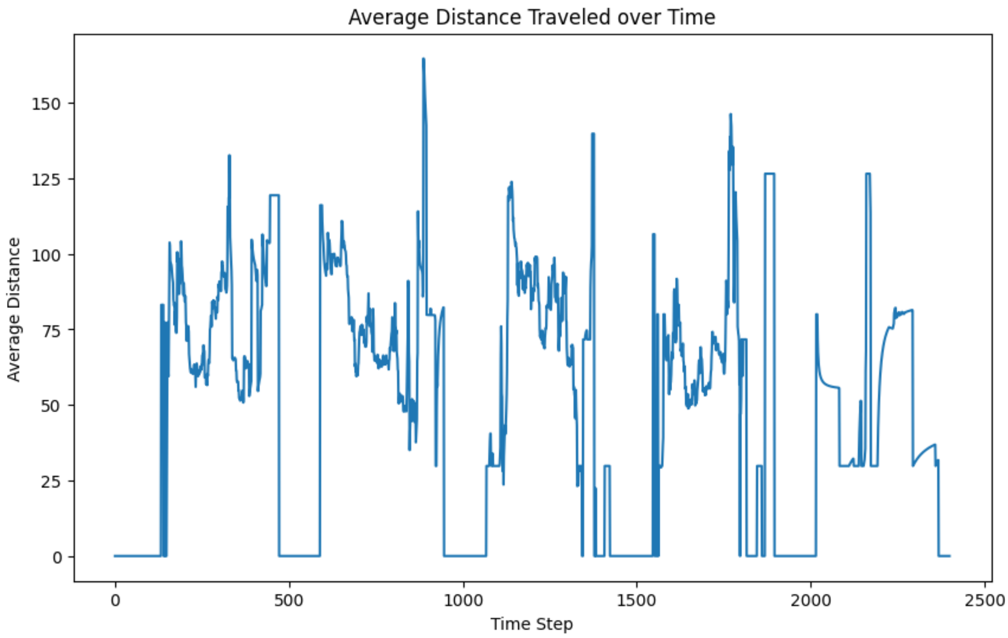

Figure 9. Average path length per simulation step for agents

Figure 9 presents the average path length in meters on the y-axis per simulation step (3 minutes) for agents throughout the simulation period. This metric provides insights into the complexity and variability of agent movements, reflecting the sophistication of the agent ontology.The graph reveals significant fluctuations in average path length over time, indicating that the agent ontology successfully captures diverse behaviours influenced by factors such as agent type, goals, and environmental conditions. The periodic nature of these fluctuations suggests a correlation with daily or weekly schedules, demonstrating the model's ability to replicate routine behaviours typical in a campus setting. Notably, there are distinct peaks in average path length, likely corresponding to transition periods between classes or other scheduled activities. These peaks indicate that the agents are capable of making longer journeys when necessary, such as moving between distant parts of the building for different lectures or activities. The valleys in the graph, representing periods of shorter average path lengths, could indicate times when agents are more likely to remain in a single location, such as during lectures or focused work periods. Additionally, during the night there are not paths, thus the value going to 0. This variation in path length over time suggests that the agent ontology successfully incorporates goal-oriented behaviour, with agents adapting their movements based on their current objectives and the time of day.

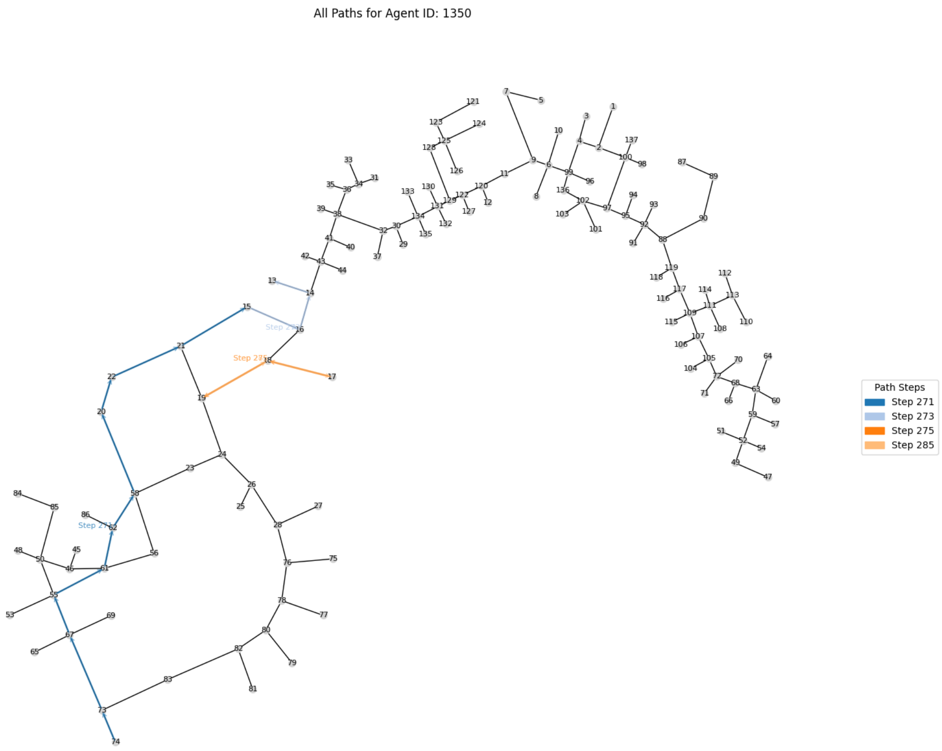

Figure 10. Example paths for agent 1350

To demonstrate the individual movement behaviour in addition to aggregate behaviour, Figure 10 illustrates the specific paths taken by agent 1350 over the course of the simulation. This detailed trajectory gives a view into the decision-making processes hardcoded in the agent ontology. The varied nature of the paths taken by agent 1350 demonstrates the the power of the agent ontology in showing realistic movement patterns by individual agents. The agent's movements show a combination of goal-oriented paths to specific destinations such as lectures and more exploratory behaviour in between these focused trips. The recurrence of certain path segments suggests that the agent has developed preferences for particular routes, possibly influenced by factors such as shortest distance, familiarity, or the attractiveness of spaces along the way. This behaviour aligns with the incorporation of memory and learning mechanisms in the agent ontology. Interestingly, there are instances where the agent takes longer, seemingly indirect routes between locations. This means that the suboptimal path behaviour is indeed activated at some points. While some of these may represent intentional exploratory behaviour or responses to changing environmental conditions, others could indicate limitations in the agent's decision-making algorithms, particularly in terms of path selection. The variety of destinations visited by agent 1350 indicates that the ontology successfully incorporates diverse goals and activities typical of a student or staff member in a campus environment. The agent's movements span different types of spaces, including lecture rooms, study areas, and possibly social or social areas. The temporal aspect of the agent's movements can be interpreted from the steps when the agent moves on the path. The seem to show realistic patterns, keeping in mind that one step represent approximately 3 real world minutes. In summary, the analysis of average path lengths and individual agent trajectories demonstrates that the agent ontology produces complex, varied, and largely realistic movement patterns. The ontology successfully incorporates key elements such as goal-oriented behaviour, memory, and responsiveness to environmental factors.

3.6 Movement behaviour and spatial factors

To address the third subquestion concerning the role of spatial factors in modeling indoor behaviour, I analyze movement flows at different times and locations within the building.

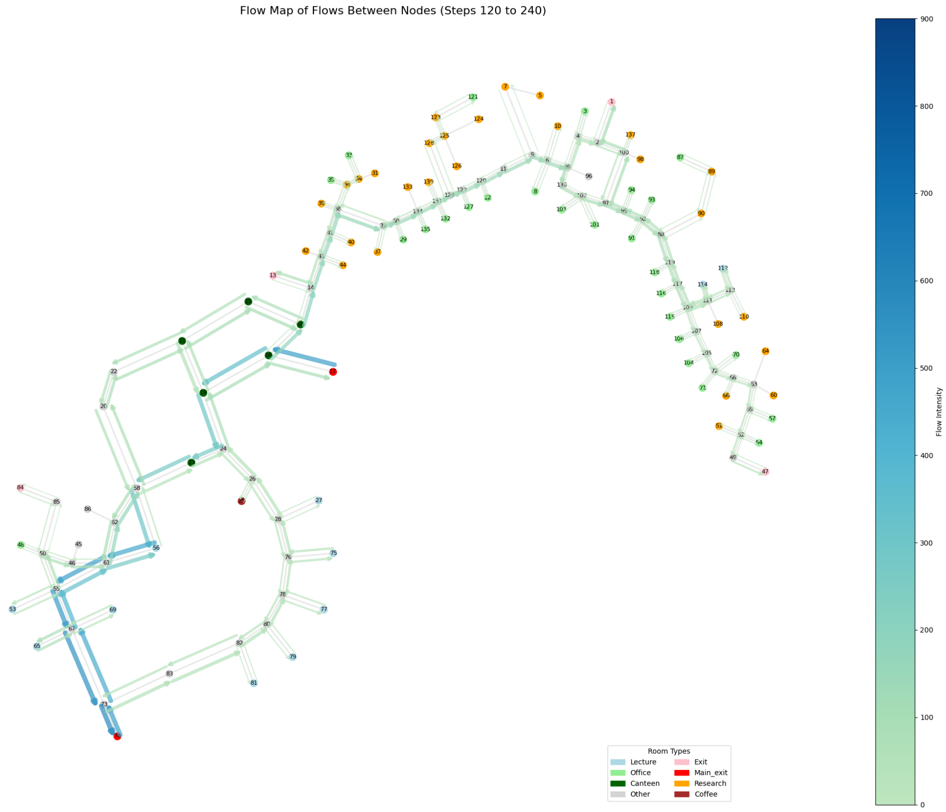

Figure 11. Flow map between steps 120-240 (around 6am - 12pm on Monday)

Figure 11 presents a flow map of agent movements between 6 AM and 12 PM on a simulated Monday. Here it can be seen how spatial layout and room functions interact with temporal factors to shape movement patterns during the morning hours. The thickness of the lines represents the volume of movement between different areas, clearly indicating preferred paths and high-traffic areas within the building. The most prominent flows are observed between entrance areas and lecture rooms, reflecting the morning influx of students. The areas near the entrances interesting bidirectional flows, representing a transitional spaces that agents pass through to reach other destinations. The balanced nature of these flows suggests that these area serves both as a destination and a place to go through. Some areas, such as those near the offices or smaller lecture rooms show relatively lighter traffic. This could indicate specialized spaces like research labs or offices that are accessed by a smaller, more specific group of agents, or areas that become more active later in the day. The overall pattern reveals a clear structure to the morning movements, with distinct patterns showing up. This suggests that the model successfully captures the influence of building layout and room functionality on agent behaviour, producing realistic flow patterns that align with expected morning activities in a campus setting.

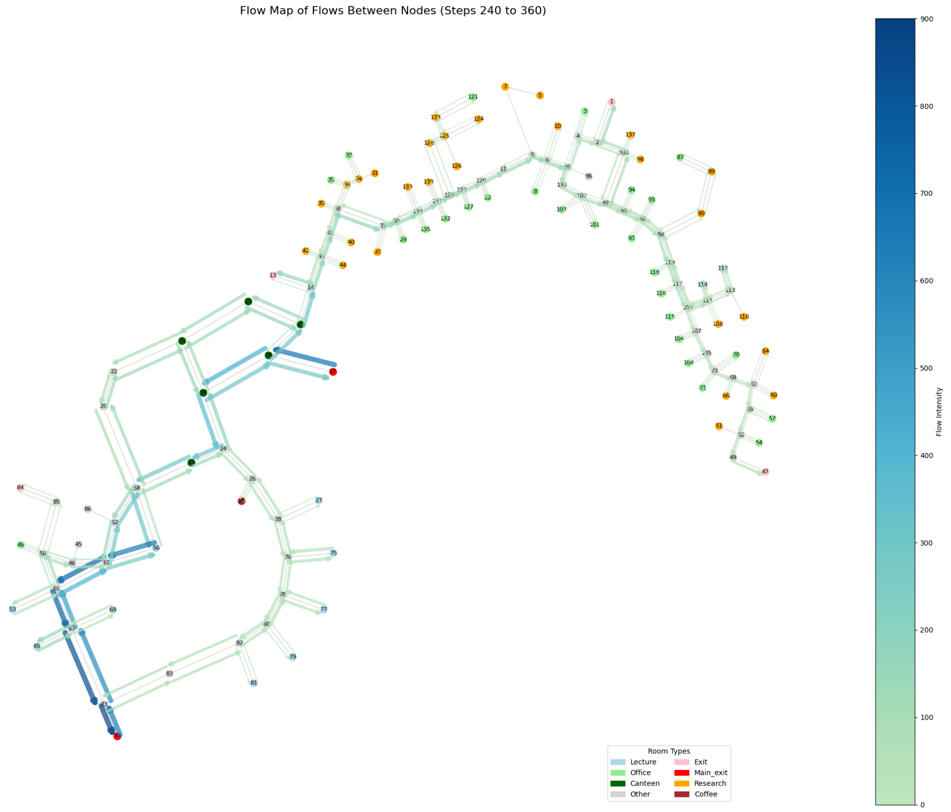

Figure 12. Flow map between steps 240-360 (around 12pm - 6pm on Monday)

Figure 12 illustrates the flow map for the period between 12 PM and 6 PM on the same simulated Monday, contuing the comparison in how movement changes throughout the day. In contrast to the morning flows, this afternoon period shows a more distributed pattern of movement. The flows appear more balanced across different areas of the building, suggesting more diverse activities as the day progresses. A notable feature is the strong flow towards and around the area 'canteen', which wasn't as prominent in the morning map. This shows that despite the problems with attractiveness, that the model does capture lunchtime behaviour. The areas that were major morning destinations continue to show activity, but the flows appear more bidirectional. This could indicate a mix of new agents arriving for afternoon classes, while others are leaving after morning activities. The overall pattern in this afternoon period suggests a more varied use of the building space compared to the morning. This aligns with the expected diversity of activities in a campus environment during peak hours, including classes, research, group work, and social interactions.

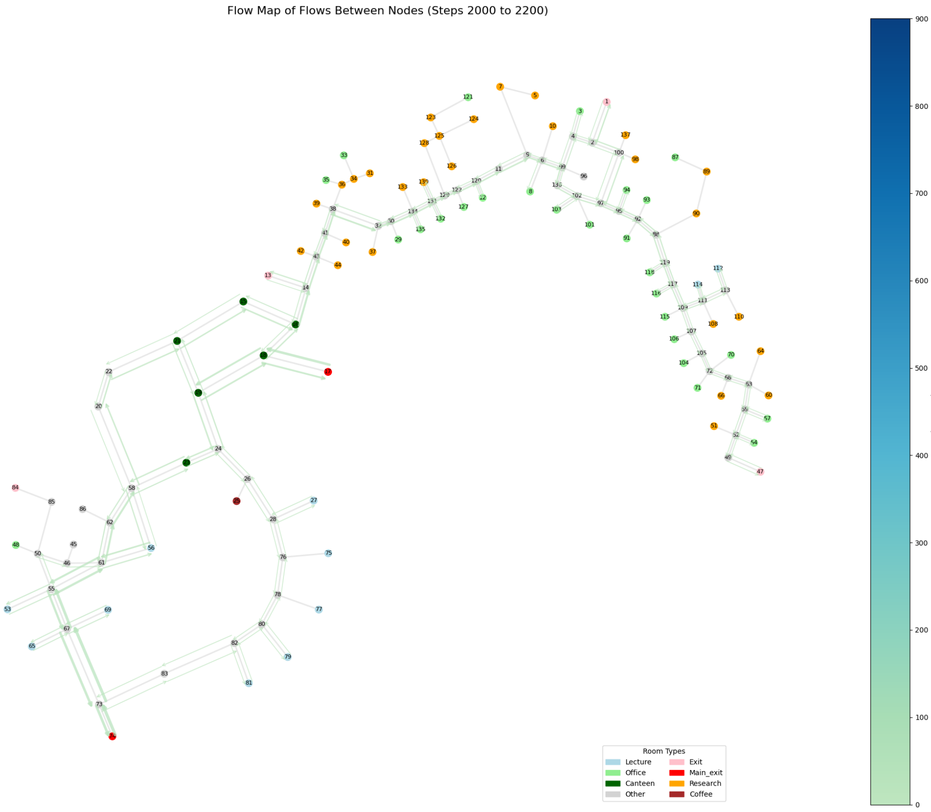

Figure 13. Flow map between steps 2000-2200 (around 4am - 2pm on Friday)

Figure 13 provides a flow map for a period on Friday, offering a comparison point to assess how movement patterns might differ later in the week and over a slightly different time range. The most striking feature of this map is the overall reduction in flow volumes compared to the Monday maps. This is particularly evident in the early hours (4 AM to around 2 PM), where flows are minimal, accurately reflecting the expected low activity during these hours. It is expected as the total occupancy for this specific Friday is lower. The flows appear more evenly distributed, with less pronounced convergence on specific areas. This would indicate that the movement is more balanced due to less contextual factors such as lectures affecting the attractiveness of specific rooms. The variation in flow patterns between Monday and Friday demonstrates the model's capability to capture day-specific behaviours and schedules. This temporal sensitivity is crucial for accurately simulating the dynamic nature of campus life throughout the week.

Across all three flow maps, it is observed that spatial factors play a significant role in shaping movement behaviours. The building's layout, the functionality of different spaces, and their relative positions all influence the flow patterns. High-traffic corridors and popular destinations consistently show up, while the usage patterns of other areas fluctuate based on time of day and day of the week. However once again, it's important to note some limitations in the analysis. The flow maps represent aggregated data and may obscure some of the finer-grained individual behaviours. Additionally, while these maps provide valuable insights into general movement patterns, they don't capture the full complexity of factors influencing individual agent decisions, such as personal preferences or responses to outlier events.

In conclusion, the analysis of spatial factors through these flow maps reveals that the model successfully incorporates the influence of building layout, room functionality, and temporal factors on agent movements. The patterns align well with expected behaviours in a campus environment, demonstrating a realistic usage of space that varies both throughout the day and across different days of the week. This supports the effectiveness of this approach in modeling indoor movement patterns while maintaining individual privacy, as these insights are derived from aggregated movement data rather than tracking specific individuals.

3.7 Sensitivity analysis

To assess the robustness of the model and understand the impact of individual parameters on the simulation results, this research conducted a comprehensive one-at-a-time (OAT) sensitivity analysis. This analysis involved varying each parameter independently while keeping others constant at their optimal values.

Table 3. Summary of Sensitivity Analysis Results

Parameter	Sensitivity	Primary Effects
memory_influence	Moderate	Decreases MAE
social_influence	Low	Increases avg_path_length
distance_decay_factor	Moderate	Increases MAE, Decreases avg_moves, Increases avg_path_length
office_avoidance_factor	Moderate	Decreases MAE, Decreases avg_path_length
research_avoidance_factor	Moderate	Decreases MAE, Increases avg_path_length
lecture_size_influence	High	Increases MAE, Decreases avg_moves, Decreases avg_path_length
base_movement_chance	Moderate	Increases MAE, Increases avg_moves
student_leave_chance	Low	Minimal effect on key metrics
lecture_leave_chance	Moderate	Increases MAE
after_hours_leave_chance	Moderate	Increases MAE, Increases avg_moves
canteen_leave_chance	Moderate	Decreases MAE, Increases avg_moves, Decreases avg_path_length
study_area_leave_chance	Moderate	Increases MAE
research_leave_chance	Low	Decreases avg_path_length
coffee_leave_chance	High	Increases MAE, Decreases avg_moves
other_area_leave_chance	Moderate	Decreases MAE, Increases avg_path_length
social_group_prob	Low	Increases avg_moves
social_group_size_min	Moderate	Increases MAE, Decreases avg_moves, Decreases avg_path_length
social_group_size_max	Low	Increases avg_moves, Decreases avg_path_length
employee_ratio	High	Decreases MAE, Increases avg_moves, Increases avg_path_length
employee_ratio_variation	Moderate	Decreases MAE, Decreases avg_moves, Decreases avg_path_length
exit_chance	Moderate	Decreases MAE, Increases avg_moves
movement_probability	Moderate	Increases MAE, Decreases avg_moves
lecture_base_attractiveness	Low	Decreases avg_moves

Figure A shows the sensitivity of the model to changes in each parameter across multiple metrics. The y-axis represents various metrics including Mean Absolute Error (MAE), average moves, average path length, and others, while the x-axis shows the range of values tested for each parameter.

The analysis revealed varying degrees of sensitivity across different parameters. The memory influence parameter showed high sensitivity across multiple metrics. Increasing memory influence tends to decrease MAE, suggesting improved model accuracy. However, it also increases average path length, indicating that agents with stronger memory tend to explore more of the building.

The social influence parameter demonstrated moderate sensitivity. Higher social influence appears to increase average moves and path length, likely due to agents being more influenced by the locations of others in their social groups. This highlights the importance of social dynamics in shaping movement patterns within the building.

Interestingly, the model showed relatively low sensitivity to the distance decay factor for most metrics, except for average path length which decreased with higher values. This suggests that while the distance decay factor affects individual movement patterns, it has less impact on overall model accuracy.

The office and research avoidance factors showed varying degrees of sensitivity. Higher avoidance factors tended to decrease average path length for students, as expected, but had complex effects on other metrics. This complexity underscores the black-box like interplay between space preferences and overall movement patterns.

The lecture size influence parameter demonstrated nonlinear relationships with several metrics, particularly MAE. This highlights the complexity of how lecture dynamics affect overall building occupancy patterns and suggests that optimal lecture sizes influence may exist for maximizing model accuracy.

As expected, the base movement chance strongly influenced average moves and path length, with higher values increasing both. However, its effect on MAE was less pronounced, suggesting that overall accuracy is robust to changes in base movement probability. This indicates a certain level of model stability in capturing general occupancy patterns despite variations in individual movement frequencies.

Various leave chance parameters (e.g., student leave chance, lecture leave chance) showed moderate to high sensitivity, particularly affecting average time in building and MAE. This underscores the importance of accurately modeling when and why agents leave different areas of the building, as these decisions significantly impact overall occupancy patterns.

Table 3 provides a summary of the sensitivity analysis results, highlighting the most sensitive parameters and their primary effects on model metrics.

This sensitivity analysis provides valuable insights into the model's behaviour and helps identify which parameters are most critical for accurate simulation of indoor movement patterns. Parameters with high sensitivity, such as memory influence and social influence, warrant particular attention in future data collection and model refinement efforts and are a good area for future research which looks at what exactly is important for modeling indoor behaviour.

Moreover, the analysis reveals complex interactions between parameters and model outcomes. For instance, the non-linear relationships observed with some parameters (e.g., lecture size influence) highlight the need for careful calibration to find optimal values. As this research tries to establish the validity of this methodology, these adjustments are out of scope for now.

The relatively low sensitivity of some parameters (e.g., distance decay factor for most metrics) indicates that the model is robust to minor variations in these inputs. This robustness is beneficial when applying the model to different campus environments where exact parameter values may be uncertain.

Overall, this sensitivity analysis enhances the understanding of the model's dynamics and provides a solid foundation for future improvements and applications in various campus settings. It emphasizes the complexity of indoor movement patterns and the importance of considering multiple factors in their simulation.

4 Discussion

The results of this research demonstrate the effectiveness of my Agent-Based Simulation (ABS) model in capturing indoor movement patterns while preserving individual privacy. The model's ability to reproduce overall building occupancy and area-specific patterns, as validated against WiFi data, confirms its capacity to capture the complex dynamics of space utilization in a campus environment. This aligns with the findings of Arslan et al. (2019), who emphasized the importance of contextual information in modeling occupant behavior.

My approach to modeling room attractiveness, which incorporates both spatial and temporal factors through a modified PageRank algorithm, proves effective in simulating realistic movement flows. This builds upon the work of Jiang & Jia (2009), who found that weighted PageRank performs well in predicting aggregate flow of pedestrians in node-based graphs. The model's success in capturing the varying attractiveness of different spaces throughout the day reflects the changing dynamics of campus activities, addressing the need for dynamic representation of space utilization identified by Valks et al. (2021). One limitation to this approach that is important to note, is that some areas, particularly those labeled as 'unknown', show less definitive patterns. This suggests that the model may have limitations in accurately representing spaces with ambiguous or multi-purpose functions, pointing to an area for potential improvement in future iterations of the model.

The analysis of path lengths and individual agent trajectories reveals that the agent ontology successfully imitates realistic behaviors. Agents demonstrate goal-oriented movement, responsiveness to environmental factors, and decision-making processes that align with expected behaviors in a campus setting. This supports the findings of Raubal (2001) and Bhattacharya et al. (2013), who emphasized the importance of well-defined agent ontologies in spatial simulations. The results seen in Figure 8 also reveal some potential limitations in the model. The occasional sharp spikes in average path length could indicate instances where agents are making unnecessarily long journeys, possibly due to limitations in the pathfinding algorithm or unexpected interactions between model parameters. These anomalies, while infrequent, point to areas where the agent ontology could be refined to produce more consistently realistic behaviour.

The flow map analysis highlights the significant role of building layout and room functionality in shaping movement patterns. The model's ability to capture both individual agent trajectories (elementary tasks) and aggregate flow patterns (synoptic tasks) and how they develop based on the patterns of the building shows the differences between individual level movement and aggregate movement. The analysis of room attractiveness over time represents concept of studying the characteristics of locations in terms of objects and time. Meanwhile, the flow map analysis corresponds to their focus on relations among locations in terms of objects and times. This multi-level approach, enabled by Andrienko et al. (2011) taxonomy, enables a comprehensive understanding of indoor movement patterns while maintaining privacy. In addition, the model successfully replicates expected variations in space usage across different times of day and days of the week. This temporal sensitivity is crucial for accurately simulating the dynamic nature of campus life throughout the week.

There are limitations to the results provided by the flow map analysis. As seen in Figures 9, 10, 11 and 12, the density of paths in certain areas, particularly around the center of the mapped space, suggests that the agent may have a bias towards central locations. This could be a realistic representation of building usage patterns, but it also raises questions about whether the model adequately encourages exploration of more peripheral areas. This is most likely to the calculation of room attractiveness.

The sensitivity analysis reveals the complex interplay of factors influencing movement patterns, with parameters related to scheduled activities (like lectures) and agent composition showing particularly high impact. This underscores the importance of accurately modeling these elements in campus simulations, as suggested by Klugl & Rindsf¨user (2011) and Kaziyeva et al. (2021) in their studies on agent-based models for spatial movement.

The identified optimal parameter values suggest a model that balances various influences on agent behavior, prioritizing purposeful movements driven by scheduled activities and space functionality while still incorporating social and memory elements. This aligns with the DNAS (drivers, needs, actions and systems) ontology proposed by Arslan et al. (2019) for understanding occupant behavior in relation to contextual information.

However, it's important to acknowledge the limitations of this approach. While the model generally performed well for most areas, some spaces showed discrepancies where the model performed worse than random guessing. This could be related to validation data issues or misrepresentation of the real space in the model. Additionally, the assumption of rational agent behavior, while necessary for modeling purposes, may not always reflect the complexities of human decision-making in real-world settings. Additionally, the focus is on a single university building, which may limit the generalization of the results. The use of WiFi data as a proxy for occupancy may not capture all movement, particularly in areas with poor signal coverage, or errors in estimating which areas people actually are in. Additionally, the model assumes rational decision-making by agents, which may not always reflect real-world behaviour.

Despite these limitations, the findings of this research not only address my research questions but also provide valuable insights for campus planning and management. The model offers a privacy-conscious method for understanding and optimizing indoor spaces, potentially informing decisions on space allocation, scheduling, and building design. This addresses the growing emphasis on privacy in smart building solutions, as highlighted by Ahmad et al. (2021) and Sun et al. (2021).

5 Conclusion

In conclusion, this research has successfully modeled indoor movement patterns in campus environments while protecting individual privacy. The established method for privacy-aware indoor movement pattern detection shows promise in capturing realistic movement patterns at the level of a single building.

One of the main contributions of this study is the incorporation of a modified PageRank algorithm to model room attractiveness. While the use case differed from the inspiration gained from Chin & Wen (2015), who used Distance-Decay PageRank (DDPR) to calculate flows of people between major cities, their implementation of spatial elements into the algorithm proved useful in this campus context. The success of this approach in guiding agents to realistic movement and occupancy patterns underscores the potential of graph-based algorithms in simulating indoor movements.

The model's strengths lie in simulating the change in activity levels in various parts of the building based on room usage type and agent composition. Interestingly, the finding that distance plays a relatively small role in this context challenges some assumptions about spatial factors in indoor movement. However, this could be attributed to the small size of the building used in this research, and results might differ when simulating an entire campus.

The success in representing agent ontology with limited parameters demonstrates that agent behavior can be effectively modeled for studying movement patterns. This allows for the examination of abstract agent behaviors instead of relying on individual private data, addressing the main research question about the feasibility of realistic representation while preserving privacy.

Looking ahead, this research opens up several avenues for future work. The model could be expanded to include more types of campus buildings or entire campuses. Investigating the impact of seasonal changes or special events on movement patterns could provide further insights. Additionally, deeper exploration of social aspects of movement, such as the influence of friend groups, could enhance the model's realism.

From a practical standpoint, the insights from this research could inform smarter decision-making about campus spaces, from the placement of study areas to class scheduling and even building design. As universities and other institutions seek ways to optimize their spaces and improve user experiences, approaches like this one could contribute to creating more socially and environmentally sustainable and efficient campuses without compromising user privacy.

In essence, this research demonstrates the possibility of modeling indoor movement patterns in a way that is both insightful and respectful of privacy. By combining agent-based simulation with smart use of aggregate data, it provides a means to understand space utilization without tracking individuals. This research provides a step towards understanding indoor movement patterns in a privacy-conscious manner. Its potential applications extend beyond campus environments to other complex indoor spaces such as hospitals, shopping centers, or office complexes. By offering a methodology that respects privacy while providing valuable insights, this study leads the way for more efficient, sustainable, and user-friendly indoor environments without sacrificing for building users' privacy.

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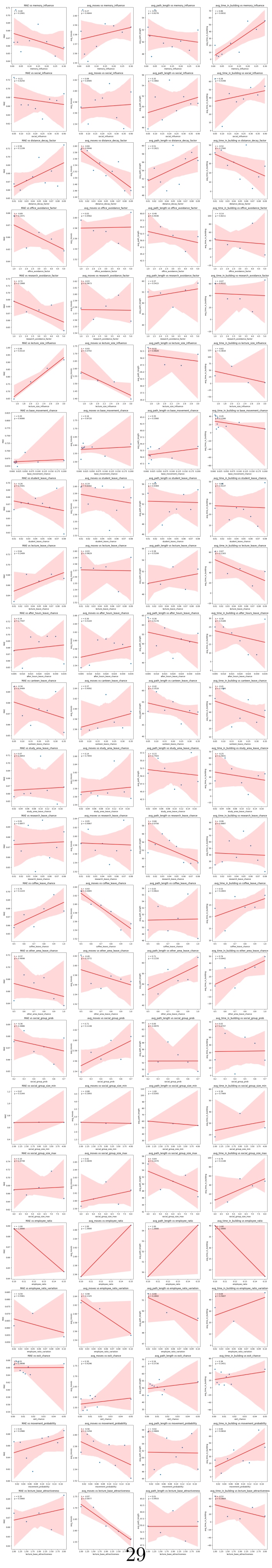
A Sensitivity analysis



B Code and data availability

Code used to create this simulation is available on GitHub at https://github.com/elqniemi/thesis-people-flow. Results data is available in the same repository. Source data is available on request.