# TOWARD A MOVEMENT PARADIGM FOR ARTIFICIAL HUMAN AGENTS

Thomas Clemen
Nima Ahmady-Moghaddam
Daniel Glake
Ulfia A. Lenfers
Florian Ocker
Daniel Osterholz
Jonathan Ströbele

Department of Computer Science
Hamburg University of Applied Sciences
Berliner Tor 7
20099 Hamburg, GERMANY
thomas.clemen@haw-hamburg.de

## ABSTRACT

The behavioral logic of agents in agent-based simulation models is becoming increasingly complex. This intrinsic development calls for new approaches to understanding and analyzing agent behavior. For example, when applying an agent-based model (ABM) without knowing the full model specifications, its agents – particularly their decision-making processes – are a black box to the user. Similarly, when designing an ABM, the individual steps of an agent's decision-making trajectories might cease to be fully traceable when the model becomes sufficiently complex. Under such circumstances, ABM users and designers are forced to infer underlying reasons for behaviors from observation. This process is comparable to ecologists observing the behavior of organisms. In this contribution, we focus on the movement behavior of spatially explicit human agents. We reflect on the Movement Ecology Paradigm (MEP) and transfer some of its conceptual results to the world of human agents. Notably, we outline the MEP's Why-Where-How complex and assess whether these three questions are sufficient for describing human agents' underlying motivations for movement behaviors. A first, basic version of the Human Agent Movement Paradigm (HAMP) is proposed. Like the ODD protocol in ecology, the HAMP can be seen as an initial step toward a standard protocol to describe the movement of spatially explicit agents.

**Keywords:** Human Agents, Multi-Agent Systems, Movement Behavior, Validation.

## 1 INTRODUCTION

Spatially explicit software agents that represent individual humans are fundamental when creating artificial societies for mobility studies of smart cities, pedestrian evacuation scenarios, the spread of infectious diseases, and many other areas. These agents are supposed to mimic human behavior authentically. "Movement of an organism, defined as a change in the spatial location of the whole individual in time, is a fundamental characteristic of life" (Nathan et al. 2008). This statement is undoubtedly also valid for humans. Therefore, movement behavior of humans needs to be addressed accordingly. In some fields of application, e.g., pedestrian dynamics, movement research is extensive (Zhong et al. 2022, Zhou et al. 2010). However, we still lack a general framework for studying why, how, where, and when human agents move.

In this paper, we compare aspects of movement ecology described mainly by the Movement Ecology Paradigm (MEP) (Nathan et al. 2008) with aspects of movement of human agents. By addressing different aspects of movement and their implications to the modeling and simulation of human agents, we propose a first version of the Human Agent Movement Paradigm (HAMP). This framework aims to give a constructivist orientation when developing artificial societies with spatially explicit human agents. Additionally, the HAMP might support decision-makers from different fields when working with simulation tools that were not been developed by themselves. In this case, model users interact with the model as a black box. This forces them to deduce motivations, reasons, and other aspects of agent behavior from observation – similar to how ecologists study animal movement.

We first reflect on research contributions from ecology and neighboring fields by briefly introducing the MEP (Section 2). By addressing the aspects of the MEP that we find most relevant for describing the movement behavior of human agents (and adding some further topics) (Section 3), we build the fundamental part of the HAMP (Section 4). Furthermore, we applied the HAMP to an existing urban traffic model to evaluate its potential (Section 5). We finalize this paper by offering first conclusions and suggested future research directions (Section 6).

## 2 THE MOVEMENT ECOLOGY PARADIGM (MEP)

Animal movement is highly demand-driven, i.e., affected by the need for food and water. Additionally, the risk of predation, reproduction, and other social interactions can trigger movement. "A movement trajectory may be understood as a spatio-temporal signal, which carries information on the complex dynamic system, i.e., the individual organism, behind" (Dodge et al. 2016). The MEP (Nathan et al. 2008) advocates a cohesive, mechanistic approach to describe the movement of organisms (Baguette et al. 2014). An illustration of the MEP's components and the associations between them is provided in Figure 1. The authors propose that movement paths of an organism are the outcome of interactions between four essential components: the internal state $w_t$, the navigation capacity $\Phi$, the motion capacity $\Omega$, and the external state of the environment $r_t \in R$. The first three components comprise the Why-Where-How complex, with $w_t$ containing the organism's motivations for movement (*why*), $\Phi$ determining *where* the organism can move to, and $\Omega$ describing *how* the organism can move.

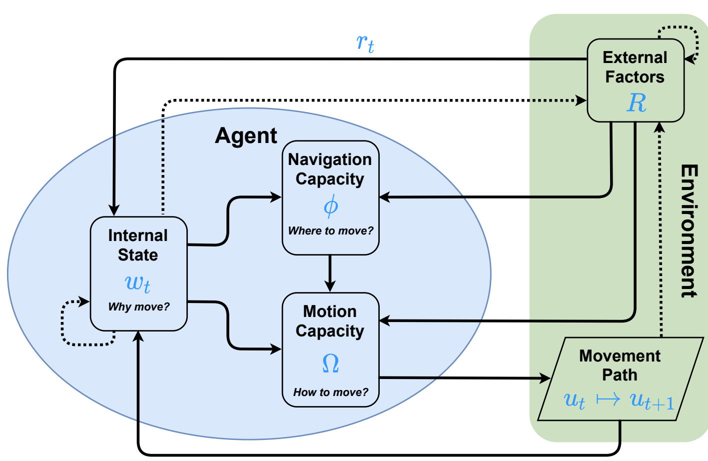


Figure 1: The MEP framework for animal movement (redrawn and changed from Nathan et al. 2008).

Let $u_t$ be the current position of an organism at the time $t$. Without limitation of generality, the next position can be described as:

$$u_{t+1} = F(\Omega, \Phi, r_t, w_t, u_t) \tag{1}$$

Please note that this equation supports both the description of steps ($u_{t+1} \neq u_t$) and stops ($u_{t+1} = u_t$). $F$ is a composite function with the following components: the motion processes $f_M$, the navigation part $f_N$, and the movement progression processes $f_U$. With that, the location transition function can be rewritten as:

$$u_{t+1} = f_U(f_M(\Omega, f_N(\Phi, r_t, w_t, u_t), r_t, w_t, u_t)) \tag{2}$$

The subterm $f_N(\dots)$ creates a map of possible $u_{t+1}$ together with weights or probabilities. $f_M$ selects an element from this map, incorporating $\Omega$, $r_t$, $w_t$, and $u_t$. A special case arises when $f_N(\dots) = id_f(\dots)$, i.e., when movement is generated without navigation. In such a case, Equation 2 can be simplified to:

$$u_{t+1} = f_U(f_M(\Omega, r_t, w_t, u_t)) \tag{3}$$

It should be noted that the MEP comprises more than described here. But for the purposes of this study, this brief description should be sufficient. We refer to Nathan et al. (2008) for further details.

## 3 SELECTED ASPECTS OF HUMAN AGENTS' MOVEMENT BEHAVIOR

Intelligent software agents (Wooldridge 1999) form the fundamental concept of multi-agent systems (MAS), agent-based modeling and simulation (ABMS) (Macal 2016), and agent-based models (ABM) (Bonabeau 2002). From the beginning, the symmetry between spatially explicit agents and their environment has been emphasized (Wooldridge 1999). It is therefore valid to observe such systems similarly to how ecological systems are observed. Research on agent-based software systems is very extensive and the variety of application is still growing.

### 3.1 Why Human Agents Move

The MEP suggests that the intrinsic motivation for an individual to move is described by its internal state $w_t \in W$. That, in turn, is represented by the state variables and properties of an agent, e.g., its date of birth, gender, or experiences.

In MARS and other frameworks, the agent performs a behavior routine during each simulation time step, typically defined in a `tick()` method. What specifically happens in this method depends mainly on the underlying architecture (Russell and Norvig 2010). Generally, the behavioral complexity can range from Simple Reflex Agents whose behavior is governed by control sequences (`if-then-else` rules) up to Learning Agents that incorporate reinforcement learning (RL) or other machine learning strategies (Hayes et al. 2022). Likewise, Logical (knowledge-based) Agents use formal systems such as modal logic or temporal logic (Shoham and Leyton-Brown 2009) to develop an internal representation of their environment by inferring logical truths and falsehoods based on their experiences.

Irrespective of the chosen modeling approach, human behavior routines can, if viewed at an appropriate temporal scale, be summarized in daily activity plans. For each day, a human can devise a set of tasks that are ordered chronologically along a timeline. With respect to movement-based behavior, a typical activity in a daily plan can consist of travelling from one place to another within a certain time frame. Applying this notion to the `tick()` routine of a human agent, one reasonable approach to modeling human behavior routines is to develop a daily plan for the agent. A human agent can then query this plan and, depending on the in-simulation time of day, pursue the applicable task or activity. This can make for a well-organized behavior routine and efficient modeling process. However, when modeling a behavior routine as a sequential execution of the activities listed in a daily plan, the agent's behavior is effectively determined. It becomes deterministic. That violates the agent's autonomy, a core principle of the ABM paradigm.

A more favorable approach might be to model the daily plan as merely another resource of the agent. As such, an agent's daily plan can be a contributor to – rather than the determinant of – the agent's decision-making process. It would become one of many sources of information, enabling the agent to deviate from it as needed. In Figure 2, this idea is illustrated by listing the daily plan along with other internal resources. The horizontal arrows indicate directions of influence: the agent's internal state $w_t$ can influence certain internal resources, e.g., the structuring of the daily plan, and vice versa. Likewise, the agent's behavior influences and changes the environment – here shown for simplicity as a set of external factors $R$ – which, in turn, exerts an indirect influence on the agent's internal resources. This interplay occurs repeatedly as the agent moves through the simulation via the `tick()` routine, indicated by the circular arrow.

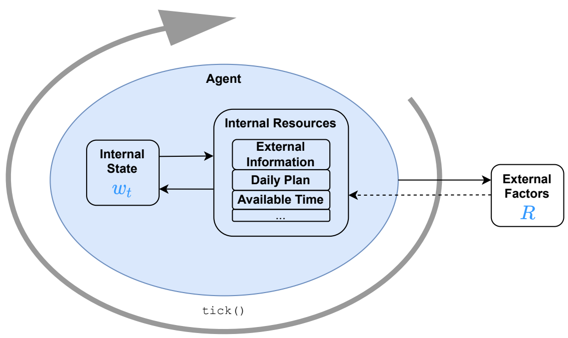


Figure 2: Illustration of the interplay between an agent's internal state $w_t$ and its internal resources, as well as the environment's external factors $R$. The agent's daily plan helps the agent organize its activities along a time axis, but does not determine the agent's behavior sequence.

### 3.2 Where Human Agents Move to

Within the MEP, this question triggers the evaluation of the function $f_N(\Phi, r_t, w_t, u_t)$. The question of where a natural individual or a human agent moves to in the next time step, relates to its own capabilities $\Phi$, its internal state $w_t$, its current spatial location $u_t$, and the state of the environment, described here as an aggregated value $r_t$.

In the natural world, it is assumed that animals and humans move by intention, e.g., to find food, to follow social and cultural demands, or to rest and sleep. Thus, the question of where agents move to is entirely linked to their internal state and the availability of appropriate locations to fulfill the needs.

Movement without navigation as described by Equation 3 also seems to occur often in the human (agent) world. Being a passenger in a car or using public transport leads to a situation in which the moving individual plays no active role in steering and navigation.

### 3.3 How Human Agents Move

Unlike natural organisms, human agents can theoretically comprise unlimited movement capabilities. In practical modeling, natural movement occurs by walking. Alternatively, mobility modalities can be chosen, generally separated into two classes, namely active and passive ones.

Lenfers et al. (2021) described an example of multi-modal switching. Human agents arrive at a subway train station in Hamburg, Germany. This first part of the trip is passive since the passenger agent does not control the train. After leaving the station building, the agent needs to walk to its final destination to rent a shared bike (if available) or choose another active modality.

## 3.4 The Role of the Environment

In ecology, the spatio-temporal distribution of resources shapes essential processes, e.g., population dynamics or species interactions (Abrahms et al. 2021). Animal movement is the primary link between these processes. This concept is directly transferable to humans, since most of us follow a daily plan (see Section 3.1) and are driven by an intrinsic urge to fulfil personal needs, as defined by $w_t$. If an agent finds that a given need cannot be met in its immediate vicinity, it can query its environment for information about where the need can be met.

For example, in an urban simulation, an agent that wants to go for a walk might decide to plan a trip to a park. This involves querying the environment for pertinent information, such as the weather and the location of the nearest park. Having this information helps the agent assess the feasibility and possibility, respectively, of its intended activity. The process of finding a route from the agent's position to a chosen park can be considered an act of *global planning*. In this process, only general features of the environment are queried – such as the road network as a whole. Once the agent is en route, a process of predominantly *local planning* takes over, wherein the agent queries the environment for specific information about its nearby surroundings (e.g., the street segment it is currently on). The distinction between global and local planning and the different goals inherent to these processes – pathfinding and navigation, respectively – illustrates that the environment can play a different role for the agent, depending on the agent's needs and activities.

ABMs can resort to georeferenced data to populate an environment with points of interests (POIs) that represent real-world places. When the model's purpose is to capture a specific part of the world, integrating georeferenced data from that part of the world into the model can increase its authenticity. Likewise, however, it creates a dependency between data quality – especially validity and integrity – and the model's descriptiveness.

The issue of data quality and availability is illustrated in Figure 3. In a model that aims to capture the urban environment of Hamburg, Germany, a set of different types of POIs can be integrated into the model to account for certain places in the city that agents might want to visit. However, the ability to integrate such data depends on data availability. Some data might be available and correct (Valid POI), while some might be available but incorrect (Invalid POI). Incorrectness can occur when, e.g., a POI has a wrong set of geocoordinates – placing it at another location relative to where it is located in reality. In Figure 3, this is indicated by the offset between the Invalid POI and the blue, transparent marker which represents the actual geocoordinates of the location represented by the red marker. Other data still might not be available at all (Missing POI), creating a data-based gap between the model and its real-world pendant.

Such gaps in accuracy and completeness affect the scope of movement-based agent decision-making and behavior that can be expressed by the model. A human agent in the model might never plan and make a certain trip – that is otherwise conceivable in the real world – because the necessary georeferenced data are not available in the model. Therefore, while georeferenced data can enrich a model's environment, it can limit the scope of behavior if the agents' behavior model is highly coupled to environmental features.

Additionally, the environment is an essential component in describing change. The growths of cities, for example, continually leads to road network adjustments, i.e., buildings and POIs appear and disappear over time. Anthropocentric and climatic changes induce changes in the natural environment. The behavior of agents should be capable of recognizing and adapting to these changes appropriately (Lenfers et al. 2018).

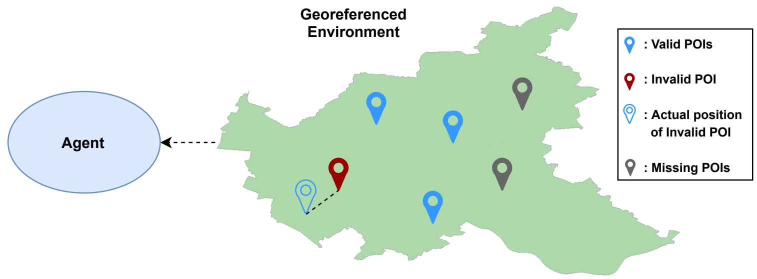


Figure 3: Illustration of how data quality – specifically, validity and integrity – can affect an agent's decision-making process and behavior. The outline of the environment represents the geographic extent of the city of Hamburg, Germany. A Valid POI represents a location with geocoordinates that the corresponding real-world location. The Invalid POI represents a location with geocoordinates that do not match its real-world counterpart. This is indicated by the offset to the blue, transparent marker. A Missing POI is a place that is not captured by the model, but that exists in the model's real-world counterpart.

### 3.5 Social Norms, Groups, and Cooperative Behavior

Recent studies emphasized the necessity to include social norms (Diallo et al. 2021) and social groups (Zhou et al. 2010, Münchow et al. 2014) into intelligent human agents in order to generate more relevant and accurate evaluations and insights. Evidently, the way people move is impacted by cultural aspects, norms, and whether they are members of a social group. We refer to Diallo et al. (2019) for a comprehensive overview of this important issue of ABMS.

### 3.6 Initializing Virtual Societies

Macal et al. (2018) describe a set of challenges that arise when creating a synthetic population (SP) of human agents. An SP aims to faithfully reproduce actual social entities, individuals, and households, as well as their characteristics as described in a population census (Namazi-Rad et al. 2014) or other sources of demographic data. Jiang et al. (2022) presented an integrated approach for creating SPs of human agents in urban settings by incorporating demographic properties, social networks, and geodata.

When working with stakeholders, policy decision-makers, or students, a frequently asked question is how many agents are needed for achieving representative and reliable results. Such a question is often rooted in a need to reduce complexity and manage computational performance by, e.g., downscaling the parameters of an actual population in order to design an SP of that population. This raises a dilemma of representativeness as a function of scale: For example, is an SP consisting of 1 000 human agents sufficient to model the system dynamics of a real-world population of 1 000 000 individuals? Likewise, given a small-scale model that appears to represent a certain phenomenon adequately, to what extent can an upscaled version of it still capture the same phenomenon? Both directions of such scaling issues require a stronger research focus in the future.

## 4 A HUMAN AGENT MOVEMENT PARADIGM (HAMP)

Given the apparent similarities between the general movement of animals and that of humans or human agents, we derive the Human Agent Movement Paradigm (HAMP) from the core properties of the MEP described in Section 2. The HAMP is a conceptual framework for designing and analyzing simulation models that include human agents.

### 4.1 The Why-Where-How Complex

The MEP's concept of the internal state $w_t$, the navigation capacity $\Phi$, and the motion capacity $\Omega$ are sufficient for being applied to human agents. In fact, these three core elements of the MEP were the catalyst for this study. It should be noted that asking *why* an agent moves at a given time to a given location by utilizing an existing movement capability is necessary for any validation effort – however, the specific agent is internally and technically structured.

As stated in Section 3.1, the internal state $w_t$ of an agent is changed over a series of discrete time steps. It appears reasonable to incorporate the agent's past internal states $w_1, w_2, \ldots, w_{t-1}$ and experiences into the computation of $w_t$. This is different from observing animals, where the current state can only be inferred from current and past observations rather than from past internal states – which are unknowable to an external observer. We, therefore, add a memory component to the scheme of the human agent.

Random movement, unlike purposive movement, is commonly used in ABMS. Jiang and Jia (2011) evaluated the differences and similarities of movement patterns that result from either random or purposive moves on a given street network. Surprisingly, they found no significant differences between these two movement types. However, more and deeper research is needed on the impact of the Why-Where-How complex to the simulation results in various domains.

Based on these reflections, Figure 4 shows a first version of the HAMP. The green rectangle represents the environment similar to that in the MEP. Each agent comprises an internal structure, shown for one agent in the blue ellipsoid. Unlike an animal in the MEP's description, human agents in the HAMP share a common environment. This allows for interactions, such as meeting, being involved in a conflict, engaging in social bonding, and establishing social groups. These and similar activities are assumed to have impacts on the simulation of artificial societies.

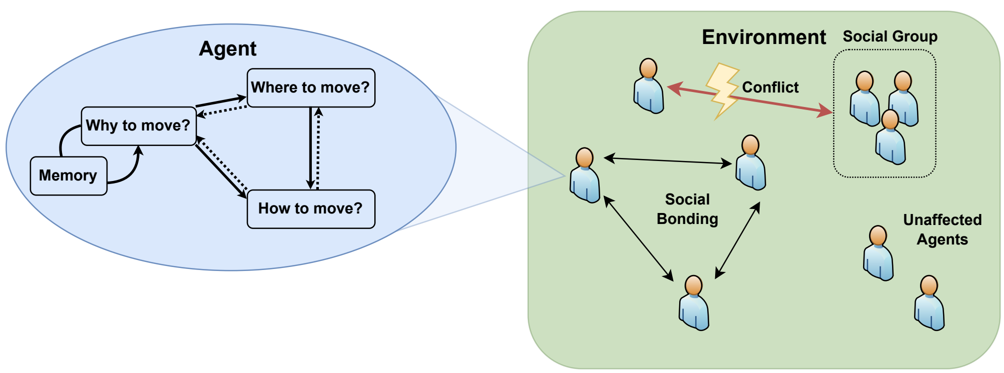


Figure 4: A general conceptual framework for the movement of human agents, designed for building and observing artificial societies. Within the agent model, solid arrows represent direct influence, whereas dashed arrows represent indirect influence.

### 4.2 The Fundamental Role of the Environment

Perceptions of the environment shape mobility decisions (van der Vlugt et al. 2022, Kim et al. 2019). Therefore, it seems reasonable to consider the role of the environment submodel in HAMP in shaping movement behavior on par with the internal state, navigation capacity, and movement capacity of the agents. Specifically, we suggest that environmental complexity cannot be expressed appropriately by $r_t$ alone. This is further motivated by the importance of data quality and integrity (see Figure 3) when designing ABMs with data-dependent environments. The tradeoff between, on the one hand, enriching an ABM's by feeding real-world data into it and, on the other hand, making an ABM's simulation outputs prone to inaccuracies or limitations due to data quality issues requires further research.

### 4.3 Cooperative and Collective Behavior

"[T]he general question is how to predict trajectories or collective movement patterns in space and time across spatial and temporal scales" (Miller et al. 2019). We do not think that it is generally possible to predict trajectories of individual human (or animal) movement precisely. Even when considering only the next few steps, too many parameters need to be accounted for. However, by executing simulations of a non-deterministic model many times, general trends might become observable. Additionally, by continuously incorporating real-time sensor data into running simulations, the corridor of uncertainty that is inherent to forecasting and prediction can be reduced significantly (Lenfers et al. 2021).

Sampled and simulated trajectories can be seen as ordered sets $\{u_0, u_1, \ldots, u_N\}$, where $N$ is the number of spatial positions, i.e., "steps" of an individual. These trajectories are seldom identical to each other, which leaves the validation question unaddressed. However, changing the perspective from actual data to a time-frequency domain, i.e., by applying wavelet transformations, might open new opportunities for validation (Polansky et al. 2010, Clemen 2000).

MAS are what the name suggests: multiple agents forming social groups, artificial societies, cultural communities and so on. The MEP, however, describes individual organisms, whereas one of the system-theoretical advantages of MAS is the ability to model interactions between agents, leading to self-organization and the formation of emergent patterns.

In the MEP, the internal state $w_t$ unidirectionally influences the navigation capacity $\Phi$ and the Motion Capacity $\Omega$ (see Figure 1). But it is known from human behavior analysis and personal experiences that the question of "how to move" (i.e., $\Omega$) also influences the question of "where to move" (i.e., $\Phi$). Therefore, for human agents, we suggest a symmetric and balanced triangle of direct and indirect influences between $w_t$, $\Phi$, and $\Omega$ (see Figure 4).

## 5 APPLICATION OF THE HAMP TO A MULTI-MODAL TRAFFIC MODEL OF HAMBURG

The ABM SmartOpenHamburg (Lenfers et al. 2021) is a large-scale, multi-modal mobility decision-support system of the traffic network of Hamburg, Germany. Optionally, it can be linked to the city's sensor network, realizing a Digital Twin (Clemen et al. 2021). As a first hands-on application of the HAMP, Table 1 lists the HAMP protocol aspects and their realization in the SmartOpenHamburg system.

## 6 CONCLUSIONS

We evaluated and transferred some essential aspects of a well-accepted movement paradigm from the field of ecology to human agents in a MAS. Analyzing the movement behavior of human agents should be a vital part of validating human-agent models. In particular, when working with Learning Agents that adapt their behavior using, e.g., RL algorithms, a mere comparison between the agent's movement trajectories and collected GPS data is not sufficient to acquire trust and credibility from stakeholders and decision-makers. Thus, considering an agent as an organism that moves spatially could be an essential step to build future collaborative and explainable AI (XAI) systems (Dafoe et al. 2021).

While the MEP was designed for understanding movement behaviors observed in animals, the HAMP intends to further the understanding of movement behaviors that are designed and observed in human agents.

Table 1: HAMP protocol for the SmartOpenHamburg model.

| HAMP aspect | SmartOpenHamburg implementation |
|---|---|
| Why to move? ($w_t$) | A. Each day, an individual activity plan is assigned to each human agent.<br>B. A typical activity can consist of travelling from one location to another within a given time.<br>C. Human agents can adaptively re-plan if necessary. |
| Where to move? ($\Phi$) | A. Movement is mainly driven by individual demands.<br>B. Demands are represented by scheduled activities in the activity plan.<br>C. Human agents can travel to POIs in the city that serve to fulfilling the needs underlying the demands. |
| How to move? ($\Omega$) | A. The portfolio of available modality types in the model reflects those available in Hamburg, e.g., private and shared bikes, private and shared cars, trains, busses, etc.<br>B. Not every agent has access to all modality types, e.g., not every person in Hamburg owns a car. |
| The environment | A. Each modality is represented by a GIS vector layer comprising a georeferenced graph.<br>B. Each graph was extracted from OpenStreetMap (OSM).<br>C. Additional nodes and edges were algorithmically added to avoid isolated subgraphs.<br>D. A separate POIs layer that contains vector features was generated from OSM data. |
| Social behavior | A. Social groups and behaviors can be parametrized in a scenario if necessary. |

Therefore, moving from the MEP to the HAMP implies moving from observation and interpretation to construction and interpretation. As such, the HAMP should serve as a conceptual framework to help model developers and model users better understand complex behaviors of human agents. In a way, it aims to be a contribution to XAI. We hope that the HAMP might support modelers of artificial humans by creating a narrative of agent-based movement.

We can conclude that particularly the Why-Where-How complex of the MEP is precious when designing and observing human agents within a simulation scenario. However, we strongly suggest emphasizing the structure, content, quality, and correctness of spatio-temporal data as a base for environments of MAS in further research. Additionally, to capture part of the social dimension that is inherent to artificial societies, the question of "with whom" might need to be added to the Why-Where-How complex. Further research should deal with adding functional components to $F(\dots)$ that represent the environment and social factors within the HAMP.

Besides the aforementioned advantages of the HAMP related to model creation and validation, the protocol might also be valuable for describing models, similar to the well-established ODD protocol (Grimm et al. 2010) in ecological modeling. However, the HAMP addresses different aspects than the ODD protocol, which can also add another perspective to ecology models.

Lastly, a critical remark might be appropriate. Birhane and Prabhu (2021) pointed out the danger that arises from systematic biases when working with large datasets in AI. “Feeding AI systems on the world’s beauty, ugliness, and cruelty, but expecting it to reflect only the beauty is a fantasy” (Birhane and Prabhu 2021). We would like to understand HAMP as a call to more critical observation of human agents in virtual societies. The initialization by demographic datasets, the complex description of the internal logic of agents, and the validity of the underlying environment entail enormous risks for biases that might have a crucial impact on the simulation results.

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## AUTHOR BIOGRAPHIES

**THOMAS CLEMEN** is a Full Professor of Database Systems and Artificial Intelligence at the University of Applied Sciences in Hamburg, Germany. He holds a Ph.D. in Computer Science from the University of Kiel, Germany. His research interests include multi-agent systems, digital twins, spatio-temporal data, and human behavior modeling. His email address is thomas.clemen@haw-hamburg.de.

**NIMA AHMADY-MOGHADDAM** is a Master's Student of Computer Science and Research Assistant at the University of Applied Sciences in Hamburg, Germany. He holds a B.A. in Psychology from the George Washington University in Washington, D.C. and a B.Sc. in Applied Computer Science from the University of Applied Sciences in Hamburg, Germany. His research interests include human behavior modeling, multi-agent systems, and machine learning. His email address is nima.ahmady-moghaddam@haw-hamburg.de.

**DANIEL GLAKE** is a Ph.D. Student of Computer Science and Research Assistant at the University of Applied Sciences in Hamburg, Germany. He holds an M.Sc. in Computer Science from the University of Applied Sciences in Hamburg, Germany. His research interests include scalable spatio-temporal data management, modelling languages, and digital twins. His email address is daniel.glake@haw-hamburg.de.

**ULFIA A. LENFERS** is a Senior Scientist and Lecturer at the University of Applied Sciences in Hamburg, Germany. She holds a Ph.D. in Geography from the University of Kiel, Germany. Her research interests include smart cities, multi-modal mobility, digital twins, and GIS. Her email address is ulfia.lenfers@haw-hamburg.de.

**FLORIAN OCKER** is a Research Assistant at the University of Applied Sciences in Hamburg, Germany. He holds an M.Sc. in Computer Science from the University of Applied Sciences in Hamburg, Germany. His research interests include multi-modality, urban simulations, and digital twins. His email address is florian.ocker@haw-hamburg.de.

**DANIEL OSTERHOLZ** is a Master's Student of Computer Science at the University of Applied Sciences in Hamburg, Germany. He holds a B.Sc. in Applied Computer Science from the University of Applied Sciences in Hamburg, Germany, and has completed an apprenticeship as an Application Developer. His research interests include georeferenced data processing and data analysis. His email address is daniel.osterholz@haw-hamburg.de.

**JONATHAN STRÖBELE** is a Master's Student of Computer Science and Research Assistant at the University of Applied Sciences in Hamburg, Germany. He holds a B.Sc. in Technical Computer Science from the University of Applied Sciences in Hamburg, Germany. His research interests include data integration, spatio-temporal data, and digital twins. His email address is jonathan.stroebele@haw-hamburg.de.