Communication and Negotiation to Improve Agent-Based Models

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Abstract: Agent-based models (ABM) play a fundamental role in studying and modeling complex real-world systems, primarily relying on reactive agents. Despite their simplicity, the interactions between agents and their environment enable the simulation of diverse systems, contributing to their widespread adoption, particularly in the social sciences. Similarly, though distinct in purpose, multi-agent systems (MAS) are designed to tackle complex, diverse, and distributed problems by leveraging communication, negotiation, and coordination capabilities. Both types of approaches have been used successfully in numerous areas; the power of ABM lies in thousands of interacting agents, while MAS usually employs a smaller number of agents with more capabilities. Including MAS agents' capabilities in ABM agents allows the generation of more realistic simulations that aid in the study of the modeled systems. In this paper, we present a generic ABM model whose agents possess more capabilities, such as communication and negotiation, allowing this enhanced ABM to address more complex modeling problems. To exemplify the usefulness of this enhanced ABM, we propose to use it as a sandbox-tool to test "case-if" scenarios in a model that studies the evolution of a society's opinion on a given subject, specifically in this example, the implantation of superblocks in the city of Vitoria-Gasteiz (Spain).

1 INTRODUCTION

Science aims to understand real-world systems, their patterns, and responses to various conditions. Direct analysis is often slow, costly, or impractical, making virtual systems essential for experimentation via modeling.

In AI, agent-based modeling (ABM) is a key method to represent complex systems. ABM depicts real-world phenomena through agents, their environment, and their interactions. Agents are defined by unique variables, actions, and environmental interpretations, enabling the creation of diverse, heterogeneous societies that mirror real-world systems (Railsback and Grimm, 2019; Wilensky and Rand, 2015).

Multi-agent systems (MAS) (Dignum, 2017; Wooldridge, 2009) address complex, distributed problems by enabling collaborative strategies among agent groups, facilitating realistic interactions for solving real-world challenges. To support this, inter-agent communication languages (ACLs) have been developed (Soon et al., 2019).

While ABM focuses on social sciences and MAS on engineering, the demand for advanced ABM in social sciences is growing (Steinbacher et al., 2021). Table 1 summarizes their key differences. In this paper we will focus on the difference in agent complexity, and the negotiation, coordination, and cooperation capabilities associated with MAS.

Table 1: Key differences between ABM and MAS.

Aspect	ABM	MAS
Purpose	Study emergent behaviors.	Solve practical, problems.
Field	Research and simulation.	AI, engineering
Focus	Emergent phenomena.	Agent cooperation/competition.
Complexity of Agents	Simple rule-based behaviors.	Advanced decision-making.
Environment	Static or simplified.	Dynamic and real-time.

An ABM example requiring more complex agents is a forest fire propagation model. Fires act as agents, with the system simulating their evolution under varying atmospheric conditions. Adding agents like firefighters or fire trucks would enable analysis of their

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effectiveness in extinguishing fires, necessitating advanced communication, cooperation, and coordination capabilities to optimize resource management. Another example is modeling local fauna in an ABM, where invasive species are agents. Incorporating hunter agents who negotiate and coordinate to eradicate invasive species introduces MAS functionalities. In both cases, starting from a standard ABM with reactive agents, adding MAS-like agents (firefighters or hunters) enhances the model's ability to address complex real-world problems.

In this work, we build on a conceptual ABM developed in prior studies (Antosz et al., 2019; Antosz et al., 2020; Bouman et al., 2021; Rodríguez-Arias et al., 2024). The model represents societies based on sociodemographic characteristics and personal needs, enabling the analysis of opinion evolution on specific topics. It also highlights the influence of key group entities or individual agents whose impact on opinion dynamics is particularly significant.

The ABM was implemented using NetLogo (Wilensky and Rand, 2015), a popular platform for agent-based models but lacking MAS functionalities and goal-oriented architectures (e.g., Belief-Desire-Intention). This work enhances the ABM by: (a) equipping NetLogo agents with basic communication, negotiation skills, and interaction protocols; (b) integrating these agents into the model to enable complex behaviors; and (c) showcasing these features through a use case. The example used is citizen acceptance of a superblock project [1]. However, the enhanced ABM is adaptable to various problems and societies (Bouman et al., 2021; Rodríguez-Arias et al., 2024).

2 STATE OF THE ART

Agent-Based Models (ABMs) are widely used for modeling and simulation across various fields. In health, Escudero et al. (Escudero et al., 2016) modeled HIV transmission in New York City (1996–2012) using an ABM. In sociology, Crooks (Crooks, 2010) used ABMs with vector GIS to study residential segregation in urban settings. In emergency management, Dawson et al. (Dawson et al., 2011) developed an ABM for policy analysis to improve flood incident management.

Agents in agent-based models typically use a reactive architecture, relying on simple stimulus-response rules (Kaelbling et al., 1987). These agents perceive their environment and act without memory or planning. This approach suits models where emergent phenomena arise from numerous simple interactions, enabling the observation of collective patterns without complex individual behaviors.

Cognitive architectures mimic human cognitive processes through three components: 1) the agent's perception of the world and its ability to sense it, 2) memory for storing information, and 3) a decision-making model. A popular example is the Belief–Desire–Intention (BDI) architecture, where agents operate based on beliefs (assumed truths), desires (goals), and intentions (committed actions) (Rao and Georgeff, 1997).

Some ABMs use hybrid architectures, blending cognitive and reactive elements. This allows agents to plan and make decisions deliberatively while reacting to immediate stimuli. Hybrid architectures combine the strengths of both approaches, providing flexibility and adaptability for simulating complex systems (Guessoum, 1997). For instance, Bussmann et al. propose a hybrid architecture for autonomous mobile robots (Chin et al., 2014).

Our goal is to implement an enhanced hybrid architecture that incorporates MAS communication languages, aiming to increase the complexity and capacity of traditional ABMs.

3 THE STANDARD ABM

The original ABM (Antosz et al., 2019; Antosz et al., 2020; Bouman et al., 2021; Rodríguez-Arias et al., 2024) consists of two distinct agent types: 1) *Humats*, representing individuals in the society under study, based on the HUMAT architecture (Antosz et al., 2018); and 2) *critical nodes*, representing entities or individuals with a significant influence on the opinion dynamics of the Humats. The following subsections detail both agent types.

3.1 Humat Agents

A *Humat* must make a decision regarding the topic under study, using sociodemographic characteristics and psychosocial needs. At least three psychological needs are considered: (1) experiential needs (e.g., personal well-being), (2) values (e.g., concern for environmental quality), and (3) belongingness (e.g., social group affiliation). Each need is defined by two factors: (1) the importance I the *Humat* places on it, and (2) the satisfaction S it derives from it. For instance, COVID-19 measures like mask use and social distancing reduce virus spread but complicate social-

[1] A superblock is a group of city blocks reorganized to prioritize pedestrians over vehicles

ization and family visits. The importance individuals assign to these needs influences their decision to adhere to preventive health measures.

To represent societal heterogeneity, each *Humat* has sociodemographic properties that, along with psychosocial needs, define it. The HUMAT architecture is flexible enough to accommodate different sociodemographic properties and needs, depending on the problem being modeled (e.g., (Antosz et al., 2020; Bouman et al., 2021)).

Each *Humat* is placed in a virtual environment, which can be geographical, social, or a combination of both. By default, the model creates a 2D virtual space that can represent various settings (e.g., an office, city, or forest). Additionally, each *Humat* is part of one or more social networks, allowing it to influence and be influenced by other *Humats*.

The life cycle of a *Humat* can be divided into two main phases: (1) self-evaluation and (2) information exchange.

Phase 1. Self-Evaluation. In each life cycle a *Humat* agent must assess its internal needs in order to choose a decision or behavioural alternative that best satisfies its individual needs. This is done by calculating the overall satisfaction (O) expected from each behavioural alternative using the equation (1).

$$O_b = \frac{\sum_{n=1}^{N} S_{b,n} * I_n}{N} \in [-1,1], \quad b = 1,2 \tag{1}$$

where S is the satisfaction value of an *Humat* for a need n and a behavioural alternative b and I is the importance that the *Humat* attaches to the need n. N is the number of needs that motivate the decision-making. *Humats* will choose the behavioural alternative with the highest expected overall satisfaction.

After choosing the behavioural alternative that most satisfies their needs, *Humats* evaluate whether this alternative generates any cognitive dissonance in them. A dissonance occurs when a behavioural alternative generates positive or negative evaluations for one need and the opposite sign for the others, where the evaluation E of a particular need is calculated as

$$E_{b,n} = S_{b,n} * I_n \in [-1,1] \qquad n = 1 \ldots N, \quad b = 1,2 \tag{2}$$

resulting in a positive (E^+) or negative (E^-) evaluation. The strength of an *Humat's* dissonance is calculated following the equation (3).

$$D_b = \frac{2d_b}{d_b + c_b} \in [0,1] \tag{3}$$

where

$$d_b = \min\left(\left|\sum_{n=1}^{N} E^+_{b,n}\right|, \left|\sum_{n=1}^{N} E^-_{b,n}\right|\right),$$
$$c_b = \max\left(\left|\sum_{n=1}^{N} E^+_{b,n}\right|, \left|\sum_{n=1}^{N} E^-_{b,n}\right|\right)$$

When the strength of the dissonance exceeds a certain tolerance threshold, the *Humat* will try to act to resolve it by communicating with other *Humats* in its same social network, as described below.

Phase 2. Information Exchange. When an agent faces a dilemma due to dissonance exceeding their tolerance threshold, they seek resolution by communicating with their social network.

The persuasiveness (P) of one *Humat* over another during communication depends on: (a) the weight α, which balances an individual's opinion against external influence, (b) the trust (T) of the influenced *Humat* in the communicator, and (c) the similarity of needs (C) between them. After communication, the influenced agent's satisfaction is updated using equation (4). The α weight ranges from 0 to 0.4, ensuring an individual's opinion always outweighs external influence.

$$P_{b,n} = \alpha * T * C_{b,n} \tag{4}$$

Respect to similarity C, if the evaluation of a need n (see equation (2)) has a different sign in both agents, then the similarity of that need is 0, otherwise, it follows equation (5):

$$C_{b,n} = 1 - |I_{b,n,e} - I_{b,n,o}| \tag{5}$$

where I is the importance of the need, b is the behavioural alternative, o is the agent that influences.

After the communication, the new satisfaction value of the influenced agent e is calculated as shown in equation (6).

$$S_{b,n,e}(t+1) = (1 - P_{b,n}) * S_{b,n,e}(t) + P_{b,n} * S_{b,n,o}(t) \tag{6}$$

3.2 Critical Nodes

The second type of agent is the *critical node*, which represents influential collectives or key agents shaping opinion evolution. Examples include local media, influencers, or academic figures like professors.

Critical nodes hold individual opinions on the topic being modeled (e.g., promoting sustainable

Table 2: Critical node communication act parameters.

Parameter	Value
Behaviour	Supporter/Opponent
Reach	Integer in [0,100]
Start month	Integer in [1,12]
Start year	Integer in [1,12]
End month	Integer in [1,12]
End year	Integer in [1,12]
Frequency per month	Integer in [1,2]
Primary critical node	Any critical node
Secondary critical node	Any critical node

transportation), which can evolve over time. They influence *Humats* through communication actions, operating based on a communication plan rather than seeking to reduce cognitive dissonance.

Each critical node is defined by parameters such as the percentage of *Humats* it can reach, its geographical coordinates, and a communication plan. The social network of a critical node is determined by the *Humats* it can influence.

A communication plan consists of a series of dated communicative acts, each characterized by scope (percentage of the social network affected), frequency, and date parameters (as shown in table 2). A communicative act can be for or against one of the decisions that the *Humats* can take. Up to two critical nodes can be involved in a communication: the primary node initiates the process, while the secondary node carries out the communication through its network. An example of a communication plan in the superblock modeling case is provided in section 5.

3.3 Model Limitations

Humats are purely reactive agents, receiving communications from other *Humats* or critical nodes, updating their internal state, and responding accordingly. In contrast, critical nodes exhibit a more proactive behavior by following a fixed communication plan throughout the simulation.

While this setup allows for the analysis of simple opinion dynamics, it limits the model's ability to represent complex and adaptive behaviors. This is particularly challenging when studying scenarios requiring collaboration, negotiation, or strategic planning. For example, the current model cannot capture how agents might adapt strategies, form coalitions, or engage in negotiation. As a result, it struggles to represent real-world dynamics where agents must balance personal interests with community goals, respond to unforeseen events, or adjust based on feedback. To address these limitations, agents need communication and reaction capabilities typical of MAS.

4 ENDOWING AGENTS WITH NEGOTIATION CAPABILITIES

The goal of this work is to enhance ABM agents, enabling them to create and execute more complex plans and behaviors. This requires hybridizing the model with multi-agent system features by equipping agents with intelligence, a new architecture, and a more sophisticated communication language, as detailed below.

4.1 BDI-Like Agents in Netlogo

The first step is to convert some agents into more complex agents by implementing a BDI-like architecture. The BDI architecture consists of 3 main components (Rao and Georgeff, 1997; De Silva et al., 2020):

- **Beliefs**, which represent information about the state of the world held by the agent.
- **Desires**, that are the agent's design objectives, i.e. those goals to be achieved.
- **Intentions**, which are the tasks that are part of the agents' plan to achieve certain objectives.

Since NetLogo does not natively support BDI agents, we propose a table-based implementation where each agent maintains *beliefs* as "concept"–"value" pairs in a table, representing its perceptions of the world. *Desires* are defined by a set of beliefs the agent intends to be true.

Finally, *intentions* are managed using a First-In, First-Out queue structure, where each entry consists of a pair ("operator to use" and a "stop condition"). The operator specifies the function the agent should execute, and the stop condition determines when the intention should be removed from the queue.

4.2 Adding Communication Capacity

The second step in enhancing agent intelligence is to provide more complex communication capabilities. Currently, agents can only use the inquire/signal actions of the HUMAT architecture, enabling influence communications but not real information exchange. To address this, agents need a structure to manage and send messages, along with an agent communication language (ACL) to define them.

An (ACL) is a standard that enables agents to exchange information about plans, goals, and beliefs (Genesereth and Ketchpel, 1994). ACLs define the types and meanings of messages exchanged between agents. Most ACLs are based on speech act theory (Austin, 1975), where messages are communicative acts intended to prompt the receiving agent to take action. In this work, we use the FIPA-ACL communication language from the Foundation for Intelligent Physical Agents (FIPA).

FIPA defines a set of performatives that specify the type of communicative act, indicating the intent of messages (Wooldridge, 2009). These acts have a well-defined meaning independent of the message content (O'Brien and Nicol, 1998), as outlined in the FIPA communicative acts library specification (FIPA, 2000). The range of performatives varies from simple information exchange to requests for tasks. Along with the performative label, a FIPA ACL message includes a set of parameters, which depend on the agent's current situation for effective communication.

NetLogo does not natively support ACLs. To enable communication, we developed a library for creating and modifying messages. In NetLogo, a message is represented as a table, with the "performative" parameter being the only required attribute. The library includes functions to add additional FIPA-defined parameters, such as sender, receiver, and content, alongside the performative. This library is available at https://github.com/alejandrorodriguezarias/EnhancedABM

Each communicating agent must have functionality to manage its conversation structure and handle message exchange. A conversation records all messages sent or received under the same conversation identifier. An agent can engage in multiple conversations with different agents, or even multiple conversations with the same agent. When an agent receives a message, it is added to the existing conversation if the agent is the intended recipient, or a new conversation is initiated if it's the first message in that interaction.

Standardized communication frameworks, known as communication protocols, enable agents to exchange messages, negotiate, and make decisions efficiently. One widely used protocol is the Contract Net Protocol (CNP) (FIPA, 2002), which manages task allocation among autonomous agents in a distributed system. In the CNP (illustrated in Figure 1), an initiator agent delegates a task to one or more participants. The initiator broadcasts a request for proposals with evaluation criteria. Participants respond with proposals, and the initiator selects the best agent based on the bids, awarding the contract. The selected agent performs the task and reports back with the results.

This structured approach allows for efficient task distribution and coordination in multi-agent systems, while also promoting a competitive environment where agents can dynamically evaluate their participation based on their current state and capabilities.

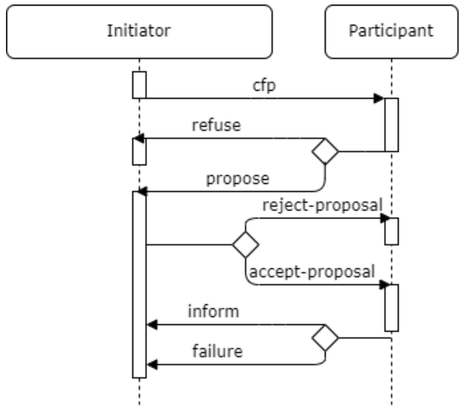

Figure 1: Contract Net protocol flowchart.

5 USING THE ENHANCED ABM: THE SUPERBLOCKS PROJECT

The original model, developed for the European SMARTEES project, has been used to analyze citizens' responses to various social innovations and simulate alternative political scenarios, such as new communication strategies by critical nodes to assess their impact on acceptance. In this paper, we apply the improved model to the case of Superblocks, focusing on Vitoria-Gasteiz, which was a pioneer in implementing this urban innovation. The project faced significant public criticism, particularly regarding policies that increased on-street parking costs. The model reflects the project's implementation (2006-2013) and was validated by stakeholders and experts in the SMARTEES project.

During the SMARTEES project, numerous promoters and detractors of social innovations contributed to ensuring the model's reliability. They proposed various scenarios to explore the social innovation from different perspectives. Despite the successful outcomes and the interesting model developed (Antosz et al., 2019; Antosz et al., 2020; Bouman et al., 2021; Rodríguez-Arias et al., 2024), some realistic scenarios could not be implemented due to the limitations of the agents, which lacked communication and negotiation capabilities. In the following subsections, we will describe the original ABM adapted to the Vitoria-Gasteiz Superblocks case and demonstrate how the agents' new capabilities enable the exploration of expanded alternative scenarios.

5.1 Virtual Environment

The model includes a virtual environment, consisting of two components: (1) the geographical environment, represented by the city of Vitoria-Gasteiz using its census sections and a 50x50 2D board (see figure 2), and (2) the social networks of friends and neighbors to which citizens belong.

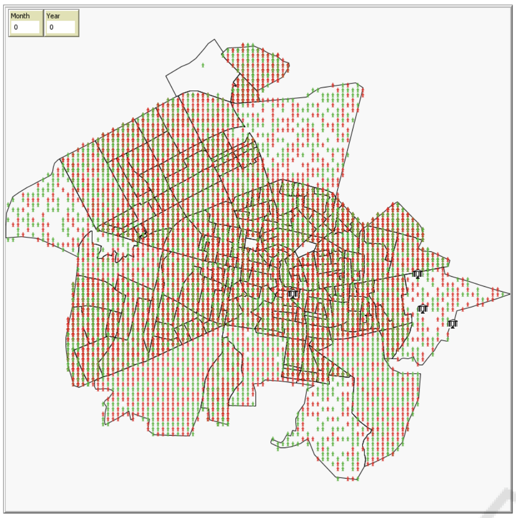

Figure 2: Vitoria-Gasteiz represented by its census sections. Citizens are represented by a human silhouette, green if they are in favour of the project and red if not. Critical nodes are represented by an image of a building.

Neighbour networks were created using social circles (Hamill and Gilbert, 2009), based on agent proximity. Friendship networks were generated as random networks with constraints: (1) a minimum number of friends per agent and (2) homophily on age and education, with a small chance of random links. Humats (see section 3.1) can communicate and influence others within their network.

5.2 Agents of the Model

In the Victoria-Gasteiz case the *Humats* represents citizens. Citizens use the HUMAT architecture for decision-making and influence diffusion (see section 3.1). These agents are initialized using data from surveys conducted in Vitoria-Gasteiz during the SMARTEES project.

As we have explained in the section 3, using HUMAT architecture we have enough flexibility to represent individuals with different sociodemographic characteristics and needs. In the table 3 we can see the properties that characterise a citizen in the superblock model. Different problems may need different characterisation, as seen in (Antosz et al., 2020; Bouman et al., 2021).

Similarly, the critical nodes are agents (see section 3.2) that represent promoters, and institutions relevant to the development of the social innovation. In the superblocks case, the following critical nodes were included:

Table 3: Variables defining a Humat agent in the superblock's project.

Variables	Values
Age (years)	integer in [18-120]
Gender	male/female
Education level	primary/secondary/ tertiary
Economic Activity	employed/jobless /inactive
Location	census tract code
Homeowner	yes/no
Years in the neighbourhood	<3 / 3- 10/ 10-30 / >30

- The city council, as the main promoter of this social innovation project.
- Merchants' associations. Throughout the implementation of the project they showed a clear rejection of the proposed measures to implement the superblocks. They were the main opponents.
- Other associations, from neighbourhood associations to cycling associations. Their opinion varied throughout the implementation of the project.
- Local press: they were the main disseminators of information about the project.

In the table 4, we can see as an example part of a communication plan employed in the superblock modeling problem. In this example, the City Council acts as a primary critical node, sometimes contracting an advertising campaign to the press (secondary critical node) to give support and promote (behavior) the superblocks project.

Critical nodes implement the BDI architecture (explained at section 4) and the necessary structure to communicate using the FIPA-ACL protocols (see section 4.2). Specifically, in this case they have the mechanisms to implement the contract net protocol.

5.3 Model Results

After the model was implemented, the lack of detailed historical data on the evolution of citizen opinion led to its validation through expert feedback in a series of workshops conducted during the SMARTEES project (Dumitru et al., 2021). Calibration and validation of the model's parameters can be found in (Rodríguez-Arias et al., 2024).

The timeline (blue curve) in Figure 3 illustrates the historical evolution of citizen acceptability, as reproduced by the model, with results averaged over 100 model executions. To develop the communication plans of the critical nodes, an analysis of the newspaper library was conducted to ensure their realism. Each cycle of the model represents 15 days in

Table 4: Example of a critical node communication plan.

Primary critical node	Behaviour	Start month	Start year	End month	End year	Frequency per month	Reach	Secondary critical node
City council	Supporter	11	2006	12	2006	1	10%	City council
City council	Supporter	1	2008	12	2008	1	1%	Local press
City council	Supporter	2	2009	2	2009	1	20%	Local press

the simulation. As shown, public acceptance was initially high, consistent with the feedback from promoters and experts. This was due to a general consensus that led to the underrepresentation of opposing viewpoints in the media discourse. Consequently, negative messages were infrequent (reflected in the limited number of communicative acts), resulting in a rapid acceptance of the superblocks. However, in November 2009, a new traffic policy was approved, introducing traffic and parking restrictions and raising public parking costs. Resistance to this policy was initially strong, particularly from the retail sector, but it diminished as the superblock was fully established and its benefits became more apparent to the public.

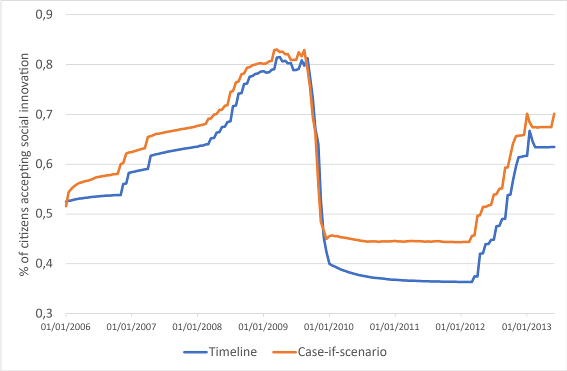

Figure 3: Comparison of the evolution of citizen acceptance between the real scenario (timeline) of Victoria-Gasteiz and the new “case-if” scenario.

5.4 Alternative Policy Scenarios

The goal of modeling superblock implementation is to provide a sandbox tool for stakeholders to test policies or ”what-if” scenarios aimed at improving citizen acceptance. These scenarios modify the real, expert-validated case.

For instance, with the enhanced BDI agents, consider a scenario where the critical node ”city council” uses this architecture to maintain citizen acceptance above 45%. It monitors acceptance levels and, if they fall below 45%, executes a plan: launching a media advertising campaign for the superblocks project. Since multiple media outlets could run the campaign, the city council uses the Contract Net Protocol to negotiate and finalize the agreement.

For that, the municipality will launch a communication to all press agents (critical nodes) requesting a two-month advertising campaign in favour of the project. Each press agent evaluates this request and communicates a proposal with two parameters: (1) the scope of the campaign and (2) the cost of the campaign. The city council will select the proposal it is most interested in and this press agent will initiate the campaign.

This scenario evaluates whether a more reactive developer can mitigate discontent during the project’s most controversial phase (see Figure 3). The CNP serves as an example of how the model benefits from enhanced agents with ACL-based communication, but other FIPA protocols could be applied. For instance, critical nodes could negotiate between cyclists and merchants opposing the superblocks project. Additionally, *Humats* could adopt BDI features to organize protest groups or political demonstrations.

6 CONCLUSIONS

Agent-Based Models (ABMs) are powerful tools for representing complex systems and are widely used in the social sciences. These models rely on reactive agents and derive their strength from the interactions between agents and their environment. However, certain phenomena require agents with enhanced capabilities to accurately capture the dynamics involved. For example, while a traditional ABM might predict the spread of a fire, incorporating agents such as firefighters who can communicate and coordinate their actions significantly enriches the model’s realism and predictive power.

We developed a NetLogo library enabling agents with a hybrid BDI (Beliefs, Desires, Intentions) architecture. This includes message generation, storage, modification, and communication via FIPA-ACL, along with negotiation protocols like FIPA-ACL Contract Net for collaboration. These agents were integrated into an ABM framework, expanding its modeling capabilities. In the presented example, the enhanced framework supports stakeholders in implementing social innovations by providing deeper insights and facilitating informed decision-making.

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REFERENCES

Antosz, P., Jager, W., Polhill, G., Jiaqui, G., Salt, D., Alonso-Betanzos, A., Sánchez-Maroño, N., and Guijarro-Berdiñas, B. (2018). Report on the conceptual model of the smartees simulation and data types to be included. Deliverable 7.1, SMARTEES project.

Antosz, P., Jager, W., Polhill, G., Salt, D., Alonso-Betanzos, A., Sánchez-Maroño, N., Guijarro-Berdiñas, B., and Rodríguez, A. (2019). Simulation model implementing different relevant layers of social innovation, human choice behaviour and habitual structures. Deliverable 7.2, SMARTEES project.

Antosz, P., Jager, W., Polhill, G., Salt, D., Scalco, A., Alonso-Betanzos, A., Sánchez-Maroño, N., Guijarro-Berdiñas, B., and Rodríguez, A. (2020). Smartees simulation implementations. Deliverable 7.3, SMARTEES project.

Austin, J. L. (1975). *How to do things with words*, volume 88. Oxford university press.

Bouman, L., Antosz, P., Jager, W., Polhill, G., Salt, D., Scalco, A., Alonso-Betanzos, A., Sánchez-Maroño, N., Guijarro-Berdiñas, B., and Rodríguez-Arias, A. (2021). Report on scenario development and experiments for selected cases. Deliverable 7.4, SMARTEES project.

Chin, K. O., Gan, K. S., Alfred, R., Anthony, P., and Lukose, D. (2014). Agent architecture: An overviews. *Transactions on science and technology*, 1(1):18–35.

Crooks, A. T. (2010). Constructing and implementing an agent-based model of residential segregation through vector gis. *International Journal of Geographical Information Science*, 24(5):661–675.

Dawson, R. J., Peppe, R., and Wang, M. (2011). An agent-based model for risk-based flood incident management. *Natural hazards*, 59:167–189.

De Silva, L., Meneguzzi, F. R., and Logan, B. (2020). Bdi agent architectures: A survey. In *Proceedings of the 29th International Joint Conference on Artificial Intelligence (IJCAI), 2020, Japão.*

Dignum, V. (2017). Social agents: Bridging simulation and engineering. *Communications of the ACM*, 60(11):32–34.

Dumitru, A., Lema Blanco, I., Albulescu, P., Antosz, P., Bouman, L., Colley, K., Craig, T., Jager, W., Macsinga, I., Meskovic, E.and Mischkowski, N., Pellegrini Masini, G., Polhill, G., Quinti, G., Salt, D., Somervail, P., and Wilson, R. (2021). Policy recommendations for each cluster of case-studies of case-studies. Insights from policy scenario workshops. Deliverable 5.2, SMARTEES project.

Escudero, D. J., Lurie, M. N., Mayer, K. H., Weinreb, C., King, M., Galea, S., Friedman, S. R., and Marshall, B. D. (2016). Acute hiv infection transmission among people who inject drugs in a mature epidemic setting. *Aids*, 30(16):2537–2544.

FIPA, O. (2002). Fipa contract net interaction protocol specification. *Document no. SC00029H*.

FIPA, T. (2000). Fipa communicative act library specification. *Change*, 2000(01/18).

Genesereth, M. and Ketchpel, S. (1994). Communications of the acm. *Software Agents*, 37(7):48–54.

Guessoum, Z. (1997). A hybrid agent model: a reactive and cognitive behavior. In *Proceedings of the Third International Symposium on Autonomous Decentralized Systems. ISADS 97*, pages 25–32. IEEE.

Hamill, L. and Gilbert, G. (2009). Social circles: A simple structure for agent-based social network models. *Journal of Artificial Societies and Social Simulation*, 12(2).

Kaelbling, L. P. et al. (1987). An architecture for intelligent reactive systems. *Reasoning about actions and plans*, pages 395–410.

O'Brien, P. D. and Nicol, R. C. (1998). Fipa—towards a standard for software agents. *BT Technology Journal*, 16(3):51–59.

Railsback, S. F. and Grimm, V. (2019). *Agent-based and individual-based modeling: a practical introduction.* Princeton university press.

Rao, A. S. and Georgeff, M. P. (1997). Modeling rational agents within a bdi-architecture. *Readings in agents*, pages 317–328.

Rodríguez-Arias, A., Sánchez-Maroño, N., Guijarro-Berdiñas, B., Alonso-Betanzos, A., Lema-Blanco, I., and Dumitru, A. (2024). An agent-based model to simulate the public acceptability of social innovations. *Expert Systems*, page e13731.

Soon, G. K., On, C. K., Anthony, P., and Hamdan, A. R. (2019). A review on agent communication language. *Computational Science and Technology: 5th ICCST 2018, Kota Kinabalu, Malaysia, 29-30 August 2018*, pages 481–491.

Steinbacher, M., Raddant, M., Karimi, F., Camacho Cuena, E., Alfarano, S., Iori, G., and Lux, T. (2021). Advances in the agent-based modeling of economic and social behavior. *SN Business & Economics*, 1(7):99.

Wilensky, U. and Rand, W. (2015). *An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo.* MIT press.

Wooldridge, M. (2009). *An introduction to multiagent systems.* John Wiley & Sons.