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An agent-based model to simulate the public acceptability of social innovations

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Abstract

The successful adoption of social innovations, such as renewable energy systems or pollution reduction plans in cities, depends, to a large extent, on the willingness and participation of the population in their development and implementation. We present an agent-based model (ABM) to analyze the process of citizen acceptability of a social innovation that uses a variety of agents to represent individual citizens and relevant groups of citizens. Citizen agents make use of the HUMAT cognitive decision-making model, based on psychosocial theories, to decide on their support for the social innovation considering how their needs will be satisfied if they decide to support (or not) the innovation project, and the influence exerted by the agents in their environment. The ABM was initially developed to represent the urban and transport planning superblock project in the city of Vitoria-Gasteiz (Spain). The ABM simulations make it possible to study the evolution of public acceptance of social innovation, with the results providing insights to the social dynamics and individual factors that affect the acceptance of the project, enabling an evaluation of how to devise new policies that increase public acceptance. Sufficiently generic to be easily adaptable to different types of social innovations, the ABM is a powerful tool to explore different scenarios and design strategies that foster the acceptance and sustainable adoption of social innovations.

KEYWORDS
agent-based modelling, artificial intelligence, HUMAT, social innovation, superblocks, sustainability

1 | INTRODUCTION

The United Nations has set out a comprehensive framework of sustainable development goals (SDGs)[1] aimed at promoting sustainable and inclusive cities worldwide. Focusing particularly on public transportation, green spaces, and sustainable urban development, these goals align perfectly with the emerging concept of the superblock. A superblock is a grouping of multiple city blocks, reorganized to prioritize pedestrians over motor vehicles. Within a superblock, traffic circulation is restricted to interior streets, while peripheral streets remain open to service and emergency traffic (Rueda et al., 2012). This urban innovation is based on a radical transformation of urban design aimed at fostering low-carbon mobility and creating high-quality public spaces for alternative social uses (Dumitru et al., 2021).

Although superblocks have significant advantages in terms of health and wellbeing, as well as increasing the number and size of green areas in neighbourhoods (Mueller et al., 2020), urban change often involves dealing with social resistance, especially to restrictions on the circulation of private vehicles. Several cities (e.g., New York) implementing superblocks (Caballero et al., 2022; Ortiz Zamora et al., 2020) can benefit by learning from pioneering cities that have already experienced radical urban transformations. Those experiences can also contribute to our understanding of specific factors, social dynamics, and innovative policy approaches that drive, inhibit, or accelerate the social acceptability of sustainable projects.

The work presented in this article was developed within the SMARTEES[2] project that proposes agent-based modelling (ABM) as a means of analysing citizen acceptability of social innovations (e.g., superblocks in cities). ABM makes it possible to analyze how sociopsychological needs impact on social innovations, thereby facilitating decision-making by promoters. Consequently, ABM is a tool of great interest, as it analyses the possible impact of new policies aimed at a population or at specific sociodemographic groups.

Although ABM was initially developed in relation to the superblock project in the city of Vitoria-Gasteiz (Spain), it is sufficiently generic to be easily adapted to other types of social innovations. For example, it has been used to model both a superblock project in Barcelona (Spain) and the acceptance of SARS-CoV-2 virus prevention measures. In addition, since the ABM agents apply the HUMAT (Antosz et al., 2019) decision-making model, citizens are represented and analysed for their sociodemographic and sociopsychological characteristics.

The paper is structured as follows: Section 2 describes the ABM state of the art; Section 3 contains a general description of ABM and its main architectural characteristics; Section 4 illustrates how ABM was adapted to the Vitoria-Gasteiz superblock project; Section 5 describes guidelines for adapting the model to other social innovation projects; Section 6 shows how social innovators can use the model as a sandbox and so enhance the acceptability of projects; and finally, Section 7 provides the main conclusions.

2 | STATE OF THE ART

In ABM, a system is modelled as a collection of autonomous decision-making entities called agents (Bonabeau, 2002). Agents may exhibit different behaviours depending on the system, for example, selling and buying in a system simulating a market. In addition, to depict global behaviour, ABM also reproduces interactions between agents and the environment, which enables complex systems and processes to be modelled. ABM has become increasingly popular, being extensively used in recent years in many different applications, including financial markets (Samanidou et al., 2007), supply chains (Baryannis et al., 2019; Blos et al., 2018), health (Badham et al., 2018; Tracy et al., 2018), and sustainability applications (Han et al., 2022).

ABM, especially suitable for the social sciences (Gilbert & Terna, 2000; Jackson et al., 2017), is the subject of a growing number of studies (An et al., 2021), as, according to Smith et al. (Smith & Conrey, 2007), the ABM approach fits well with the theoretical concerns of social psychology. In the social sciences, an agent is usually assumed to represent an individual person. Multiagent simulation, however, is a natural vehicle for incorporating the many processes studied in social psychology, including intrapersonal processes (decision-making, memory effects, personality differences, etc.) (Chaher et al., 2020; DeAngelis & Diaz, 2019), interpersonal processes (social influence, emotional contagion, etc.) (Fan et al., 2018), group processes (norm formation, leadership, etc.), intergroup processes (discrimination, intergroup anxiety, etc.) (Huet et al., 2020), and social and cultural processes (cultural transmission of concepts, innovation diffusion, etc.) (Anzola & Rodríguez-Cárdenas, 2018; Moglia et al., 2018).

The goal of the SMARTEES project, as far as ABM is concerned, is to represent different local communities and test the effectiveness of various policy measures with a view to implementing projects involving a social innovation, defined as 'a change in social relations involving new ways of doing, organizing, framing and/or knowing, and is transformative when it manages to challenge, alter, or replace dominant institutions, both formal and informal' (Caiati et al., 2019). The development of formal models that integrate social innovators is of great importance, as questions can be posed, the effect of multiple innovators interacting with each other can be simulated and explored, and the factors that influence the final impact of different innovations can be evaluated (Robinson et al., 2012).

However, to our knowledge, there are few applications of ABM to social innovations, even though the idea is not novel (Robinson et al., 2012). A search in Scopus using the keywords 'social innovation' and 'agent-based' revealed only 13 papers, and of those, 6 are associated with the SMARTEES project. The remaining publications cover various topics that are not directly relevant to our study: the potential of ABM for history (Chattoe-Brown & Gabbriellini, 2017), two-agent simulation for decision-making when selecting the optimal fare for on-demand transportation services for commuters or goods (Gerpe & Markopoulos, 2020), an overview of ABM for product development teams (Čeh et al., 2022), ABM as a technique to apply artificial intelligence to the social sciences (Kim et al., 2022), ABM as a participatory simulation tool for social innovation activities (Bok & Ruve, 2007), and the integration of multiple simulation paradigms, among them ABM, in a single simulation platform to demonstrate how cognitive household digital-twin technology can promote sustainable energy consumption (Adu-Kankam & Camarinha-Matos, 2022).

ABM underutilization in the context of social innovations is due to several factors that hinder development and adoption. Firstly, there is a lack of awareness of how useful ABM could be in this context. Secondly, since ABM requires interdisciplinary collaboration between social scientists, computer scientists, and policymakers, disciplinary divides and a lack of collaboration impede the development of robust and contextually relevant ABM. Finally, a third factor is the complexity of modelling social systems due, in large part, to the lack of a specific developmental methodology and the difficulty of finding a base model of agent behaviour. Therefore, proper collaboration is necessary to build a model that is clear, transparent, and easily explained to people with little technical or computer knowledge.

Addressing the underutilization of ABMs in the context of social innovations is crucial to advancing our understanding of complex societal challenges. We explore the potential of ABMs to address one such challenge: the superblock, an urban and transport planning social innovation. Urban development is crucial for sustainability, since cities, as hubs of economic activity and knowledge exchange, consume vast amounts of resources that contribute to the climate crisis and are responsible for massive greenhouse gas emissions that negatively affect people's health (Nieuwenhuijsen, 2016). Cities that have manageable sizes and more or less known problems (Angelidou & Psaltoglou, 2017) can exercise citizen-centric governance regarding experiments with and implementation of innovative ideas.

Many ABMs apply to urban development, rather than social innovation, although not specifically to superblocks[3]. González-Méndez et al. (2021) provides a good overview of ABM applications to urban development. To delineate 15-min cities,[4] Chen and Crooks (2021) developed an ABM utilizing realistic street networks and points-of-interest to grow diverse communities from the bottom up and estimate local community sizes; this ABM, centred on human mobility, monitors how people walk in their environment to estimate the size of a walkable community. Although the use of psychological theory is relevant to capturing behaviour in simulation models (Jager, 2017), not many ABMs include this component. A variety of recent works (Foramitti, 2023; González-Méndez et al., 2021) address the utility of considering the satisfaction of human needs. Foramitti (2023) describe a needs and limits (N&L) framework as a theoretical and computational foundation for an ABM that describes how quality of life can be enhanced by satisfying a person's needs. González-Méndez et al. (2021) propose an ABM for urban planning based on the relationship between city inhabitants and satisfaction of basic needs in their physical environment. Although both those works consider the agents that surround a central agent to be important, neither includes communicative acts between agents aimed at influencing others.

Although this paper cannot be considered a methodology for the development of ABM systems, it does make two important contributions that may inspire other researchers to use ABM to investigate similar problems: we demonstrate an ABM adaptable to different situations, and we describe the ABM development steps. In our proposal, the main action of agents is to communicate with each other and exchange opinions on the social innovation. This is important because a suitable communication strategy by the social innovation project can increase its acceptability to citizens during implementation.

3 | MODEL DESCRIPTION

Using an ABM and the creation of superblocks as an example, we explore issues related to citizen acceptability of a social innovation and how acceptability may be influenced by the actions of policymakers, the city council, the press, neighbourhood associations, and so forth. More specifically, the ABM simulates the temporal evolution of citizens' opinions regarding the social innovation and how this varies according to different policy actions. Ultimately the idea is to answer the question: what percentage of citizens will be for and against the social innovation based on different policy scenarios?

The ABM incorporates several key components (described in greater detail in subsequent sections): (a) citizens, as the main agents in the model, (b) the environment, and (c) institutions (critical nodes) playing a relevant role in the development of the social innovation. As an illustrative example, Figure 1 depicts the ABM components for the Victoria-Gasteiz superblock project to be described below. Simulating the interactions between these components generates emergent behaviours that ultimately determine the acceptability of the social innovation.

3.1 | The citizen-agent

The main ABM entity is the citizen. To reflect the heterogeneity of a population, citizens are represented as individual intelligent agents, characterized by sociodemographic and other variables. To decide their stance regarding the social innovation project, citizen agents follow the cognitively grounded decision-making HUMAT model, based on psychosocial theories (Antosz et al., 2018) and developed under SMARTEES. Agents are also individually characterized by variables reflecting their needs (such as the need for comfort or their commitment to the environment) and the importance they attach to those needs. HUMAT considers three types of basic needs: (1) experiential needs, which refer to comfort and economic aspects; (2) belongingness, or the need to feel part of a group; and (3) values, referring to biospheric or social goals. Following the HUMAT model, agents make a decision based on: (a) how their needs will be satisfied if they support (or reject) the innovation project, and (b) the influence exerted by the agents around them. Note that the HUMAT model is generic enough to adapt to the variables and needs that best describe a

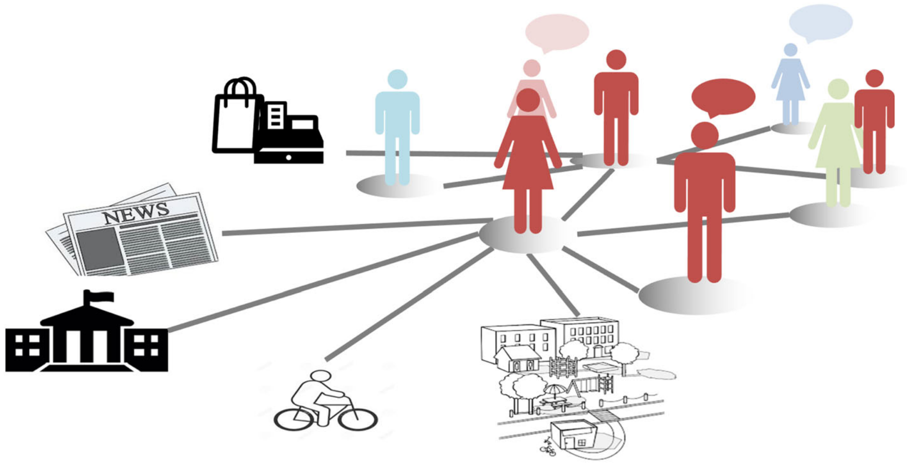


FIGURE 1 An ABM using the Vitoria-Gasteiz superblocks as an example. The human silhouettes represent the citizen agents and the lines linking the citizens are their social networks (friends and neighbours). The agents also have communication links with other key actors, namely, business associations, the press, local government, and cyclist associations.

population and the problem to be modelled (as will be seen in Section 4, describing the variables and needs used to model the acceptability of superblocks).

The HUMAT model implements a four-phase life cycle, as explained below.

3.1.1 | Phase 1: Evaluate behavioural alternatives

A behavioural alternative is defined as an option in relation to an event modelled in the ABM, for example, to be for or against the creation of a new superblock. Conceptually, the decision is influenced by two parameters—importance and satisfaction—associated with needs: (a) I is the importance a citizen attaches to a specific need, and thus, the more important a need, the more weight it will have in the final decision; and (b) S is the degree of satisfaction expected from the chosen alternative (e.g., accepting or rejecting the project). For example, if a project involves closing streets to traffic and removing parking spaces, a citizen's need for comfort (having a parking slot close to the workplace/home) would be less satisfied by acceptance than rejection of the proposal.

Accordingly, each alternative provides a certain expected satisfaction level S regarding internal needs that depends on the circumstances of each individual and their interaction with their social network. The lifecycle of a HUMAT agent starts with an analysis of these levels of satisfaction, and the decision-making process will be directed towards trying to satisfy all needs, taking into account the importance I attached to each need. The initial values for satisfaction $S \in [-1,1]$ of each need and the importance $I \in [0,1]$ attached to each need can be obtained from some external data source during model initialization (to be explained further below).

The evaluation E of the overall level of satisfaction S that a behavioural alternative b provides for a need n, which depends on the satisfaction S expected by the agent and on the importance I attached to their need, is computed according to Equation (1).

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

where N is the maximum number of an agent's needs. Satisfaction of needs will be evaluated positively $\left(E^+_{b,n}\right)$ or negatively $\left(E^-_{b,n}\right)$. The final decision of an agent is based on the expected overall level of satisfaction O for each behavioural alternative b, obtained as shown in Equation (2).

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

Cognitive dissonance may occur when an alternative evokes satisfaction regarding some needs, but also dissatisfaction regarding other needs. The strength of this dissonance is calculated as shown in 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 cognitive dissonance exceeds a certain tolerance threshold, the agent is confronted with a dilemma that requires solving. A dilemma arises when a particular need is evaluated as positive (E^{+}) while all other needs are evaluated negatively (E^{-}), or vice versa. While there may be as many dilemmas as needs, HUMAT distinguishes between dilemmas affecting belongingness and dilemmas related to any other type of need.

3.1.2 | Phase 2: Choose a preferred alternative

Based on the previous evaluation, the agent chooses between the behavioural alternatives, usually the option that generates the highest overall expected satisfaction (see Equation 2). However, if satisfaction levels are similar,[5] then the agent must explore the differences in depth:

1. If the cognitive dissonances generated by alternatives are sufficiently different,[6] then the alternative that generates the lowest dissonance is selected.
2. If the cognitive dissonances generated by alternatives are very similar, the need for wellbeing is prioritized (i.e., the hedonistic choice). Regarding a particular need, if, between the behavioural alternatives, there is a sufficient difference in satisfaction, then that which yields greater wellbeing is selected.
3. Finally, if both alternatives are practically identical, one is randomly selected.

3.1.3 | Phase 3: Act

The actions in the model are communicative acts, which, when the social innovation generates interest in the population, leads to conversations between individuals. Conversations take place to resolve possible dilemmas with respect to the selected alternative. If the agent has a belongingness dilemma, it will try to reduce its dissonance *D* by convincing other members of the social network regarding the advantages of choosing the same behavioural alternative; this act is referred to as signalling. If the agent has any other type of dilemma, it will ask for advice, information, and opinions from the other agents; this action is called inquiring. In both situations, the following conditions apply to selection of the communicative target:

1. Agents must belong to the same social network (see Section 3.1.1).
2. Preferred for signalling is an agent with an opposite opinion and, for inquiring, an agent with the same opinion.
3. The persuasiveness of the agent sending the message depends on how difficult it has been to persuade the receiving agent in the past.
4. Communication among agents must not have been recent (other than when due to a random action).

In this phase, agents have a random probability (ω) of signalling communication acts with other agents in their social network.

3.1.4 | Phase 4: Experience the effects

After a conversation, an agent updates its status based on the received communication and the persuasiveness level. Persuasiveness, reflecting the extent to which the influencing agent (the sender when signalling, the receiver when inquiring) can change the opinion of the influenced agent, depends on two factors:

1. The trust of the receiving agent in the sending agent, which does not have to be reciprocal.
2. The similarity of the needs of both agents. If the evaluations of a need n (see Equation 1) held by both agents have different signs, the value of this similarity is 0; otherwise, similarity is calculated as a function of the importance I attached by each agent to the need (Equation 4).

$$M_{b,n} = 1 - |I_{b,n,e} - I_{b,n,o}| \tag{4}$$

where b is the behavioural alternative, o is the influencing agent, and e is the influenced agent.

The persuasiveness P of the influencing agent is calculated as shown in Equation (5).

$$P_{b,n} = \alpha * T * M_{b,n} \tag{5}$$

where $T \in [0,1]$ is the trust of the influenced agent in the influencing agent, and where $\alpha \in [0,0.5]$ is an arbitrary number that ensures that the previous opinion weighs more in the final satisfaction than the opinion received during the communication. Note that P can only reach a maximum value of α when both agents have identical needs and trust in the influencing agent is maximum; the minimum influence will be 0 if the agents differ in the importance assigned to the need or if there is zero trust. Note also that, although the similarity of needs is dynamically updated as the model is run, trust between agents is static (it is fixed during model initialization and remains fixed throughout the simulation). After a communication, the new satisfaction value of the influenced agent is calculated as shown in Equation (6).

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

which reflects the fact that an agent does not radically change its opinion (in fact, its own opinion may prevail).

Table 1 summarizes the conceptual variables for a citizen agent following the HUMAT model.

3.2 | The environment

Another important element of the model is the environment in which agents are located, which, in our ABM, is a geographical representation of the city to be modelled and the social networks in which the agents interact.

The city is represented through census tracts on a 2D board of 50 × 50 cells, with each cell representing a single census tract. The use of census tracts makes it possible to generate a sociodemographic distribution of agents that coincides with the real distribution. Figure 2 shows a geographical representation of the model of Vitoria-Gasteiz census tracts, where the agents are represented by human-shaped silhouettes—in green if they are for and in red if they are against the social innovation project.

Agents have their own social networks allowing interactions between agents, defined by directed links characterized by weights representing the trust of one agent in another (as mentioned, this trust is important for communications and does not have to be reciprocal). Each agent generates two social networks: (a) a network of neighbours, and (b) a network of friends. The neighbours network is based on a proximity relationship,

TABLE 1 Variables defining a HUMAT agent.

Variables	Description
Sociodemographic characteristics	For example: age, gender, occupation, net salary, education level, marital status…
Need importance	Defines how important a need is for the citizen. For example, for an agent who highly values having parking close to home, the importance of comfort will be high. This value is used as a weight in the equations to evaluate satisfaction.
	Need values fall in the interval [0,1].
Need satisfaction	Defines how satisfied a need is for the citizen. For example, if a citizen lives in a city without pollution, their satisfaction with environmental quality will be high.
	This parameter is a numerical value in the interval [−1,1].
Trust values	One citizen's trust in another citizen is used as a weight in the influence equations.
	If a citizen does not trust another agent, they will not be influenced by them.
	Trust values are numerical values in the interval [0,1].

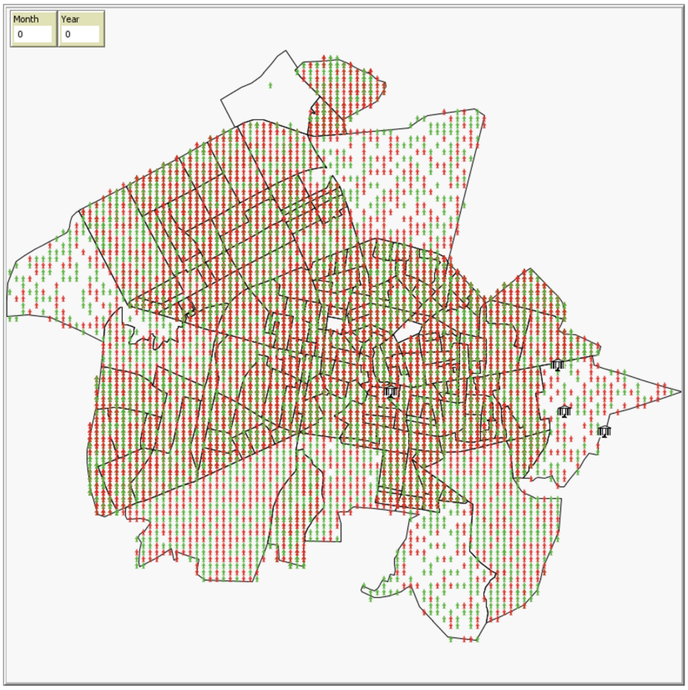


FIGURE 2 Vitoria-Gasteiz agent environment.

so the cell to which the agent belongs is relevant when forming this network. It is generated using the concept of social circles (Hamill & Gilbert, 2009), and is based on the distance between agents on the board. The relationships are reciprocal, that is, if agent A is a neighbour of agent B, then agent B is a neighbour of agent A. The friends network is randomly generated with certain restrictions: (a) there is a minimum number of friends, specific to each agent; and (b) the relationships are mainly based on homophily in age and educational level, although some lower probability relationships ignore this homophily requirement.

3.3 | Critical nodes

Critical nodes are a special type of agent that represent key organizations involved in the social innovation project (the promoters), or in its diffusion or in the generation of an influential for or against viewpoint. A critical node could be, for example, the city council, the press, or a neighbourhood association. It is defined by its name, its scope (the percentage of agents forming part of its social network), its location on the 2D board, and the trust it generates in agents (e.g., if a local press node, it will influence the agents that trust that press). The social network of a critical node is generated using a random network whose size is determined by its scope. This network is fixed at the outset and is invariable over time.

Each critical node has its own interest in the social innovation; it may be for or against it, and may even vary its opinion over time. Like citizens, a critical node can only perform communicative acts; however, its behaviour during model simulation is predefined by its communication plan, which consists of a series of dated communications that the relevant actor carried out during the implementation of the project, for example, a press campaign launched by the city council to highlight the benefit of superblocks to reduce environmental pollution. This communications are represented with a set of communicative acts defined by the parameters listed in Table 2. Two critical nodes may be involved in a communication: the primary critical node triggers the communication, while the secondary critical node is the one to which the communication is delegated. The behaviour parameter indicates whether the communication is for or against the social innovation. Reach is the percentage of the critical node's social network that is influenced by the communication. The rest of the parameters establish the timing and frequency of the communication. Table 3 lists several examples of communications by different critical nodes.

For every need n, the new satisfaction of an agent a after receiving a communication from a critical node c is defined by Equation (7).

$$S_{b,n,a}(t+1) = \begin{cases} (1-P)*S_{b,n,a}(t)+P & \text{if } b_a = b_c \\ (1-P)*S_{b,n,a}-P & \text{if } b_a \neq b_c \end{cases} \quad (7)$$

TABLE 2 Critical node communication parameters.

Parameter	Value
Primary critical node	Any critical node
Secondary critical node	Any critical node
Behaviour	Supporter/opponent
Reach (% of citizens affected by the communication)	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]

TABLE 3 Example of critical node communication acts.

Primary critical node	Behaviour	Start month	Start year	End month	End year	Frequency per month	Reach (%)	Secondary critical node
Local press	Opponent	9	2009	12	2009	2	30	Local press
Business associations	Opponent	6	2012	6	2012	1	10	Local press
City council	Supporter	1	2013	1	2013	1	10	Local press
Other associations	Opponent	1	2014	1	2014	2	30	Local press

where b_a and b_c are the behavioural alternatives chosen by a and c, respectively, and where P is the persuasion exerted by the critical node on the citizen, which depends on the trust T that the citizen has in the critical node; it is calculated as shown in Equation (8).

$$P = T * \beta \tag{8}$$

where β is a parameter that limits the persuasiveness of critical nodes.

3.4 | Execution loop

Figure 3 shows the model execution loop for a simulated evolution of the system over a given time period. The execution loop begins after the initialization phase to generate the virtual environment, agents, and social networks. The first step is for the critical nodes, according to their plan, to emit a communication whose effects would be experienced by the agents. In the second step, the agent will communicate with other agents, either randomly or to try to solve dilemmas regarding their behavioural decision. Finally, the agents experience the effects of their actions and the simulation data are updated to the end of the set period.

As an illustrative example of how HUMAT works, we take a city where a superblock is being implemented, and where one of the necessary measures is to reduce the number of parking spaces.

1. *The critical nodes launch their communications*: The local press launches a communication informing of the implementation of the measure and the impact on parking spaces. The city council issues another communication announcing how this measure will reduce pollution in the city. The citizen, who does not own a car and for whom the issue of pollution is key, receives both communications.
2. *Phase 1: The citizen evaluates their behavioural alternatives*: The previous communications will have had a positive effect on the citizen's overall satisfaction, since support for the superblock will increase their satisfaction with environmental quality (with a high weight) and reduce the need for parking spaces (with a lower weight), while producing a reduction in overall objection to the superblock.
3. *Phase 2: The citizen chooses their behavioural alternative*: As the expected overall satisfaction for the alternative of accepting the superblock is higher than for the alternative of rejecting the superblock, the citizen chooses to support the superblock.
4. *Phase 3: Friends and neighbours create cognitive dissonance in the citizen*: The citizen's network of friends and neighbours care less about pollution, as they all have cars and value parking in the area, so they decide to object to the superblock. This will generate a

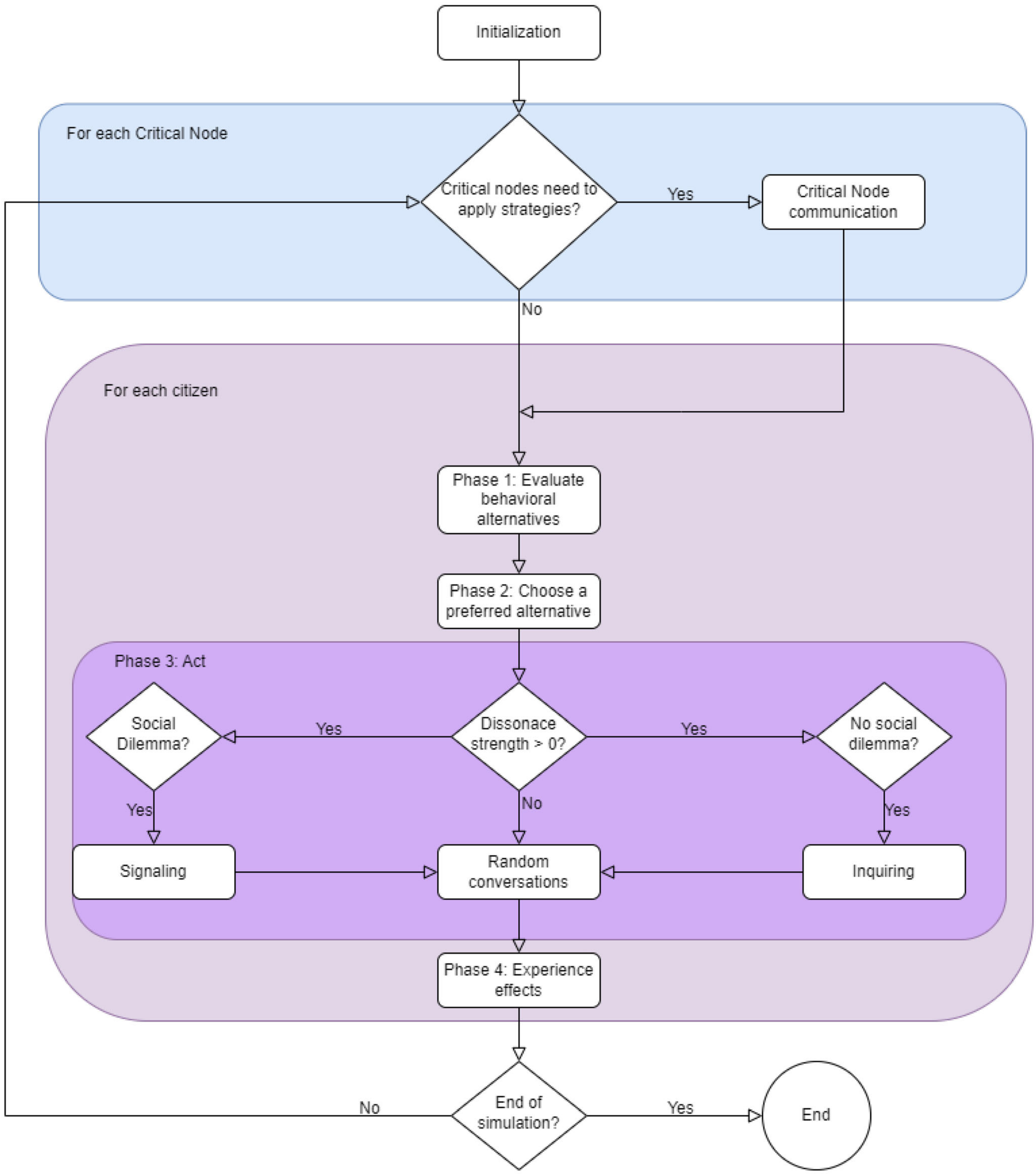


FIGURE 3 Agent-based model execution loop.

cognitive dissonance in the citizen's need for belongingness. To resolve this dissonance the citizen will try to convince the network members of the benefits of pollution reduction by communicating with a member of their network (preferably with an opposite opinion).

5. *Phase 4: The citizen experiences the effects of the communication* (following Equations 4, 5, and 6), both their own communications and received communications, and the cycle restarts.

4 | MODELING ACCEPTABILITY OF THE VITORIA-GASTEIZ SUPERBLOCK PROJECT

Using the model described above, the Vitoria-Gasteiz superblock was taken as a base case in order to model the evolution of citizen acceptance during its implementation. To model the real problem, the three main components of the model (citizen-agents, the environment, and critical nodes) need to be fed with data that reflect the characteristics of the population. Additionally, any other parameters that influence model behaviour need to be calibrated in order to adjust the model to reality.

4.1 | Data feeding

4.1.1 | Citizens: Populating the model

The model represents a heterogeneous population, and so requires individual characterization of the agents. This approach identifies the specific needs that most influence acceptance of the superblock project. It also enables interested entities to tailor their information campaigns to specific target groups with distinctive characteristics, in turn, allowing them to observe the effects of their campaigns.

To collect the data, a survey (designed by psychologists and sociologists in the SMARTEES project) was administered to the city's population. One set of questions asked for sociodemographic details: age, gender, place of residence, trust in the government, number of friends, trust in members of their networks of friends and neighbours, and so forth. Another set of questions referred to citizens' needs in relation to the superblocks, for example, how important is air quality, road safety, health, and so forth (see https://github.com/alejandrorodriguezarias/Vitoria-SMARTEES-Survey for the full version of the survey).

Table 4 shows the sociodemographic variables that characterize the citizen-agents. Information was also obtained for the trust T that citizens have in members of their networks of friends and neighbours.

Table 5 shows the different citizens' needs, materialized in six needs for the case of superblocks from the three core needs considered for HUMAT. Other questions referred to the importance attached to each need and perceptions of the level of satisfaction expected to be achieved with the superblock project.

The sociodemographic variables were filled in directly with the corresponding survey questions. However, the number of responses (865 valid responses) was less than the city population. The survey responses were dumped on agents in the system, some 'real' agents (given the 1:1 correspondence) and some 'simulated' agents (in a process described in more detail below).

To generate the population, it was impossible to take into account all possible combinations of sociodemographic variables (see Table 4) and to contrast them with the population statistics for Vitoria-Gasteiz. Therefore, a decision tree, trained following a process described elsewhere

TABLE 4 Sociodemographic variables characterizing the citizen-agents.

Parameter	Value
Age	Integer in [18,100]
Gender	Male/female
Occupation	Employed/unemployed/freelance/student/inactive
Educational level	Primary or less/secondary/tertiary
Census tract	Census tract code
Children?	Yes/no
Years in the neighbourhood	<3/3–10/10–30/>30

TABLE 5 Needs characterizing agents at the psychological level in relation to the superblock problem.

Need	Description
Wellness	Among others, refers to health and security aspects
Comfort	Facilities like parking availability and cost
Participation	Possibility of participating in decision-making
Environmental quality	Air and noise pollution
City prestige	Interest in the city's reputation
Belongingness	The human need to feel part of a group

(Alonso-Betanzos et al., 2021), was created to predict citizen responses to the question 'Will you vote for or against a future superblock in the city?'. Each leaf in the decision tree represents a profile or cluster of citizens with similar demographic characteristics and representing the majority behaviour (acceptance or rejection of the project).

Figure 4 illustrates the decision tree derived for Vitoria-Gasteiz, where the sociodemographic variables appear as nodes. 'Age' is the root variable and 'Years in the neighborhood' and 'Educational level' appear in the next level. One of the profiles that can be derived from this tree, for instance, is that people aged under 65 years who have been living in the neighbourhood for under 10 years and with a low education level have a high probability of voting against the project. The decision tree was validated by expert psychologists and sociologists working on the SMARTEES project, who found that its accuracy of 72% was sufficiently high for the complexity of the classification problem and that the conclusions that could be drawn were sufficiently plausible. The use of a decision tree was fundamental because of the great capacity of this method to clearly explain the reasoning behind predictions.

Once citizen profiles were available, they could be used to generate the simulated agents that would reflect the actual demographic profile of the city. This was done as follows:

- A total of 30,000 simulated agents were generated in accordance with the actual age and gender distributions in Vitoria-Gasteiz, available from the data for each of the census tracts.
- To complete the sociodemographic variables of the simulated agents, the survey data were categorized by age and gender, resulting in eight distinct groups representing gender-age combinations (male, female, under 25, 25–44, 45–64, and over 65). Distributions of the remaining sociodemographic variables were maintained for these groups, and this information was used to generate new simulated agents; for example, if 20%, 50%, and 30% of males aged 25–44 years have a low, medium, and high education level, then this distribution holds for simulated male agents aged 25–44 years.
- Finally, to complete the importance, satisfaction, and trust values, the simulated agent traverses the tree and falls within a particular profile (leaf node); then, cloned from a randomly chosen real agent with the same profile are the importance, satisfaction, and trust values. Thus, the values of the real agents are distributed among the simulated agents, maintaining the impurity of the node. In this way, the simulation is based on a population as similar to the real population as possible.

4.1.2 | Virtual environment

The virtual environment is the city of Vitoria-Gasteiz. To accurately distribute the agents within this environment while preserving the city's real sociodemographic distributions, representation of the census tracts was essential as these play a significant role in determining the density of the

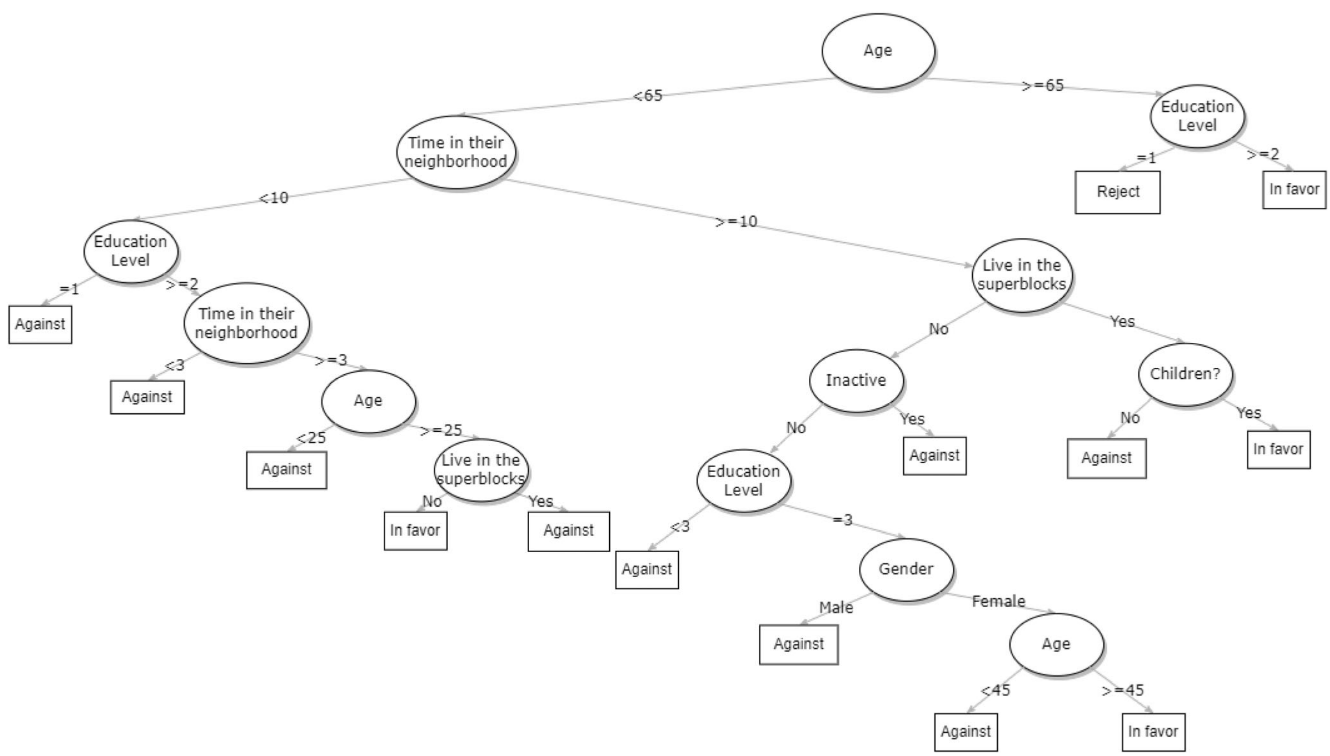


FIGURE 4 Decision tree classifying citizens in clusters.

neighbour networks in the model. Using GIS data on census tract distributions, obtained from the National Institute of Statistics, a virtual representation of Vitoria-Gasteiz was created as depicted in Figure 2.

4.1.3 | Critical nodes

Critical nodes identified for the Vitoria-Gasteiz superblock project were as follows:

- The city council, the main promoter of the superblocks.
- Business associations, the main opponents.
- Local press, reporting on events related to the superblocks.
- Other associations, mainly of residents and cyclists, which may change their mind about the superblocks during the process.

The communication plans for the critical nodes need to replicate the real communications during implementation of the superblock project. Therefore, a systematic search was conducted in news, communications, and public events carried out during the project development process. This information was analysed and contrasted in SMARTEES policy workshops (Dumitru et al., 2021, 2019; Lema-Blanco & Dumitru, 2019) organized with representatives of the critical nodes reflected in the model. Thus, real communications were translated to communications in the model according to the established communication parameters (Table 2) and so faithfully represent the real communicative acts that took place. An example of a complete communication plan for a critical node, following the details described in Section 3.1.2, can be found at https://github.com/alejandrorodriguezarias/Vitoria_Superblocks/blob/main/CriticalNodeData/CriticalNodeCommunicationPlan.csv

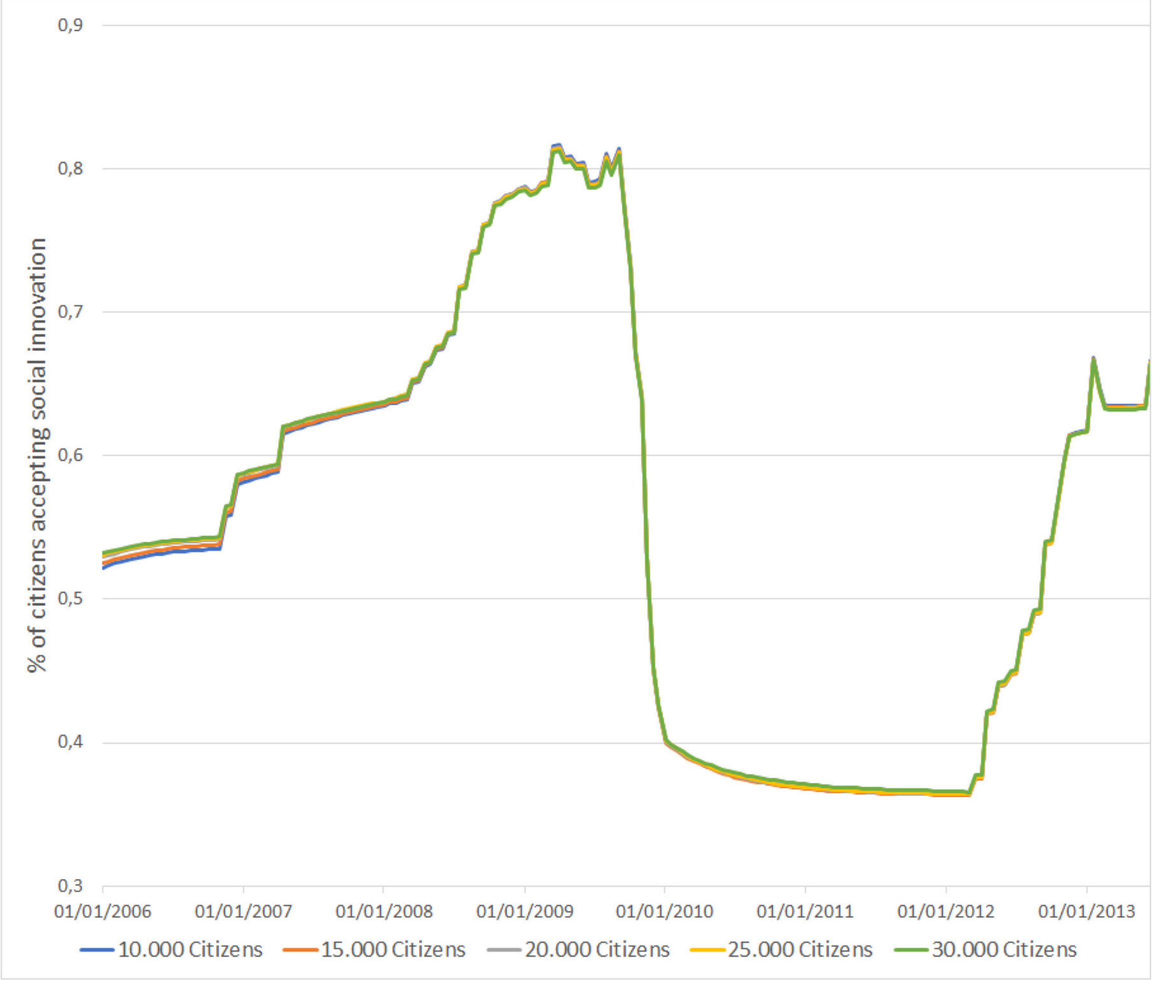


FIGURE 5 Evolution of acceptance using different numbers of citizens. Each curve reflects an average of 100 runs. The *Y*-axis shows the percentage of citizens accepting the measure on each day of the simulation.

4.2 | Sensitivity analysis

In this section we explore the impact of the model parameters on the temporal evolution of citizen acceptance using the one-factor-at-a-time (OAT) method (Bar Massada & Carmel, 2008) of local sensitivity analysis. Parameters related to agent sociodemographic data and psychosocial needs are completed with the survey data. As for data on social networks, the number of friends is obtained from the survey and constraints on link generation are set theoretically.

Five parameters remain to be determined: (a) the number of agents used in the model simulation, (b) the α parameter that defines maximum influence between two citizens (see Equation 5), (c) the β parameter that defines maximum influence of a critical node on a citizen during a communication (see Equation 8), (d) the γ parameter that indicates whether or not two values of overall satisfaction are similar, and (e) the ω probability that agents have a random conversation about the superblocks, that is, not motivated by dissonance.

To compare the effect of varying parameter values, 100 simulations were performed with each value alteration, keeping the remaining parameter values fixed. Simulations started with 10,000 agents and were increased by 5000 in each run up to a maximum of 30,000. The minimum value of 10,000 agents was chosen to ensure that no citizen was geographically isolated during citizen distribution and social network generation, and also that there were enough citizens to correctly generate friend networks; as for the maximum of 30,000 agents, this was the maximum that could be computed without the future scenario simulations lasting more than one day. Note that varying the number of agents used leads to no change in the evolution of citizen acceptance. By simulation end, the standard deviation of the percentage of agents that accepted social innovation was 9×10^{-4} and, as can be seen in Figure 5, there was no notable variation in evolution throughout the simulation.

For the parameters defining maximum influence between two agents (α) and maximum influence of a critical node on an agent (β), the simulations started with a minimum value of 0.1 and increased by 0.1 up to a maximum of 0.4. The maximum of 0.4 was set to ensure that the original opinion of a citizen prevailed over opinions received during a communication.

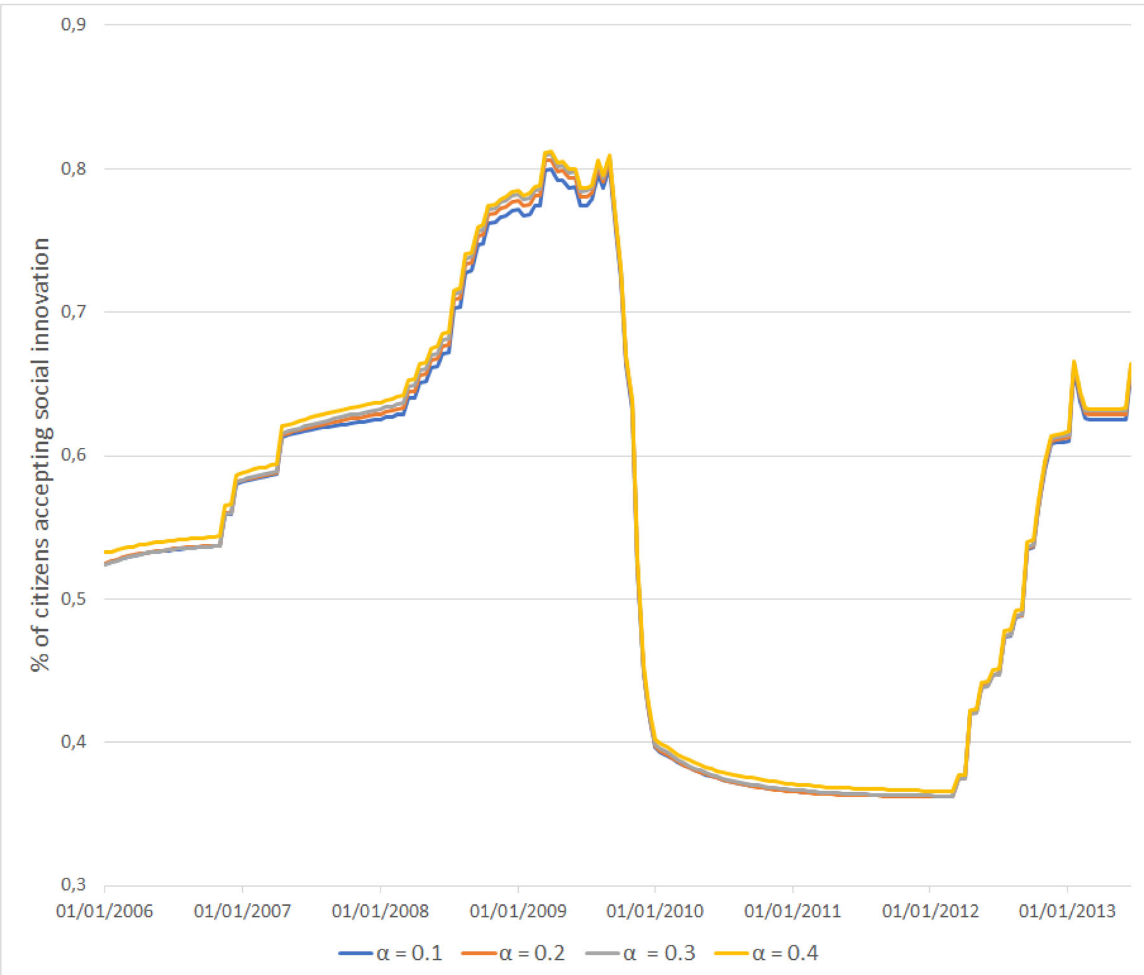


FIGURE 6 Evolution of acceptance using different values for parameter α. Each curve reflects an average of 100 runs. The Y-axis shows the percentage of citizens accepting the measure on each day of the simulation.

Figure 6 shows simulation results varying the α parameter. The greatest changes occurred in the first half of the superblock project, before the first major superblock crisis occurred (parking restrictions). Figure 7 shows simulation results varying β. As expected, the model was very sensitive to changes in the maximum influence capacity of critical nodes for each communication to an agent.

For the citizen decision threshold (γ), we started from a minimum value of 0.1, increased by 0.1 to a maximum value of 0.3, which avoided citizens choosing their behaviour randomly. Variability in acceptance based on this parameter depends on how satisfied the agent is in each cycle. Figure 8 shows that change in the evolution of satisfaction was not drastic, as could occur with other social innovations and other data.

Finally, for the ω probability that the agents have a random conversation, the simulations start at a value of 0.05, increased by 0.05 up to 0.2, so as not to flood the simulation with random communications. Figure 9 shows the simulation results, where the parameter value change especially affects the first half of the superblock project. Generally speaking, the greater the probability of communication, the more agents follow the general trend, whether for or against the superblock project.

4.3 | Calibration

ABMs contain a large number of parameters that capture complex interactions between elements in a system. While it is possible to determine some parameter values directly from information sources, other parameters need to be calibrated to obtain a good approximation to the original system—specifically, parameters to which the model is sensitive (as determined in the sensitivity analysis), namely, α, β, ω, and γ.

Due to the lack of accurate historical data on public acceptance of the superblock project during the years of implementation (2006–2013), expert validation was carried out in several workshops (Dumitru et al., 2021, 2019) conducted in the framework of the SMARTEES project and involving key superblock stakeholders. The objective of the calibration was to try to reproduce in the ABM important events that occurred during superblock implementation.

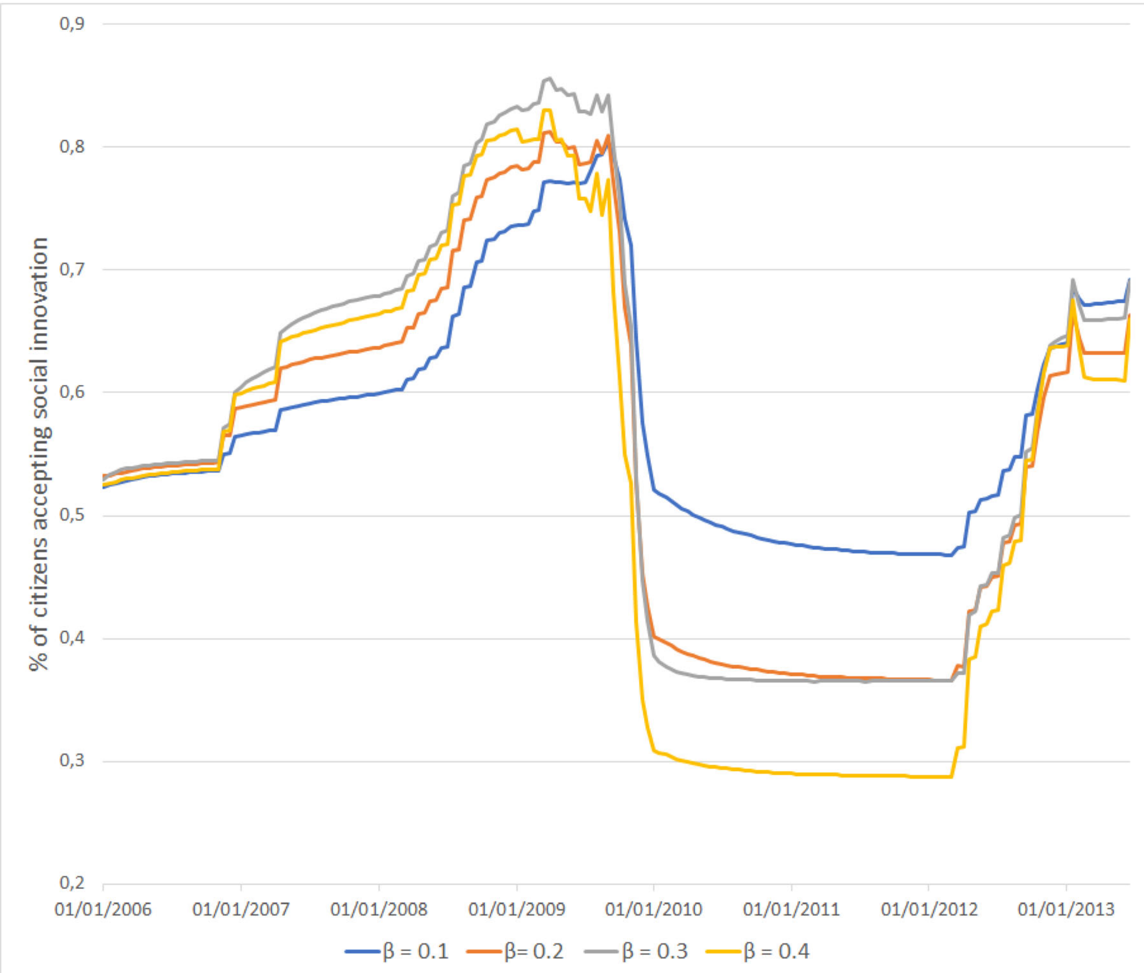


FIGURE 7 Evolution of acceptance using different values for the maximum influence capacity of the critical nodes (β). Each curve reflects an average of 100 runs. The *Y*-axis shows the percentage of citizens accepting the measure on each day of the simulation.

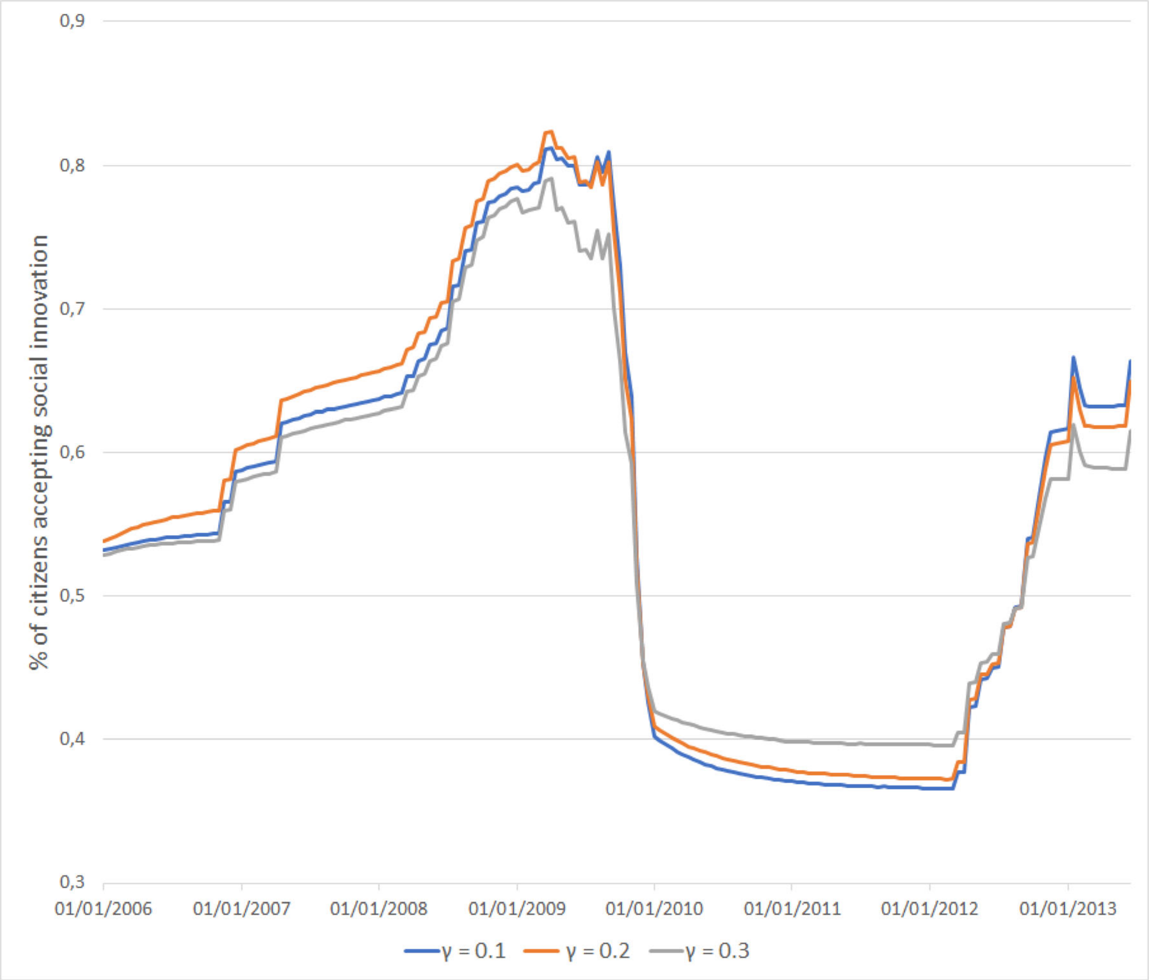


FIGURE 8 Evolution of acceptance using different values of the citizen decision threshold (γ). Each curve reflects an average of 100 runs. The *Y*-axis shows the percentage of citizens accepting the measure on each day of the simulation.

Figure 10 shows the historical evolution of citizen acceptability, obtained as an average of 100 model executions and using critical node communication plans and the agents described in Section 4.1. As can be seen, public acceptance was high at the project outset, consistent with information gathered from the promoters and experts.

The Vitoria-Gasteiz superblock project, which had been defined in the Sustainable Mobility and Public Space Plan (2007) prepared by the City Council, was supported by all political groups, relevant social groups, and the local press. The first steps involved design of a new public transport system, guided by participatory meetings with residents and neighbourhood associations. Critical node communications during this period were important in determining the evolution of citizen opinion. Note that since a certain consensus had been reached, opposing positions were underrepresented in the media discourse, which explains the low frequency of negative messages encountered in the documentary analysis (a very small number of communicative acts) and the rapid acceptance of the superblocks. However, a new traffic policy approved in November 2009 imposed traffic and parking restrictions and increased public parking costs. Resistance to this policy was initially high, especially by the retail sector, but decreased once the superblock was fully established and its benefits were perceived by the population.

In conclusion, the model accurately represented the pattern described by the experts, with parameter values set to $\alpha = 0.4$, $\beta = 0.2$, $\gamma = 0.1$, and $\omega = 0.05$.

5 | GUIDELINES FOR ABM ADAPTATION

The ABM described above, designed and developed to be as general as possible, can be adapted to a multitude of situations where the impact of social change needs to be evaluated. It has, for instance, been used to model social acceptance of the superblock project in Barcelona (see Appendix) and to model opinion dynamics regarding SARS-Cov2 vaccination (Li & Jager, 2023).

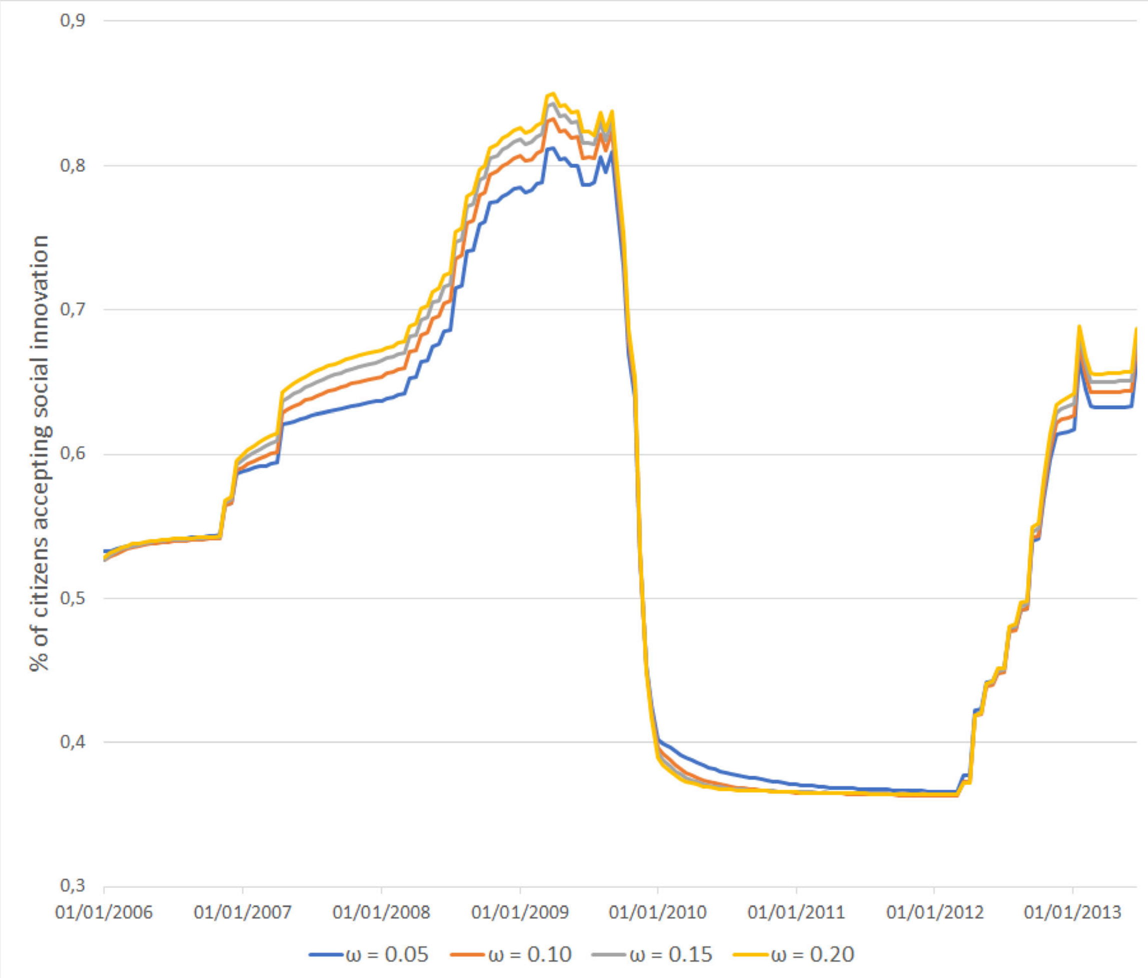


FIGURE 9 Evolution of acceptance using different values of the ω probability that agents have a random conversation. Each curve reflects an average of 100 runs. The *Y*-axis shows the percentage of citizens accepting the measure on each day of the simulation.

The following summarizes steps to be followed to adapt the ABM to a new use case:

1. Identify the social innovation measure to be modelled and define the time period.
2. Obtain data on the needs of citizens directly and indirectly affected by the social innovation (e.g., through citizen surveys).
3. Analyze the data and decide which needs are relevant and can be represented in the model.
4. Determine whether, with the data obtained, it is possible to represent a sufficient number of agents for a reliable simulation and, otherwise, generate simulated agents (e.g., using decision trees and census data).
5. Build the virtual environment, for example, using data on census tracts or some other characteristic feature of the area to be modelled.
6. In relation to influence networks, for neighbour networks, define a physical distance for which two agents are considered neighbours, depending on the size of the model and the data available (e.g., building, street, or broader neighbourhood), and for friend networks, limit the maximum number of friends, considering individual data and global population data.
7. Define critical nodes relevant to the project, such as local government, the press, associations, businesses, politicians, influencers, and so forth.
8. For each critical node, define its communication plan based on a systematic analysis of news and communications (and possibly virtual social networks) during the implementation period.
9. Implement simulations and analyze the results of model adaptation.
10. Validate the results against the actual process.

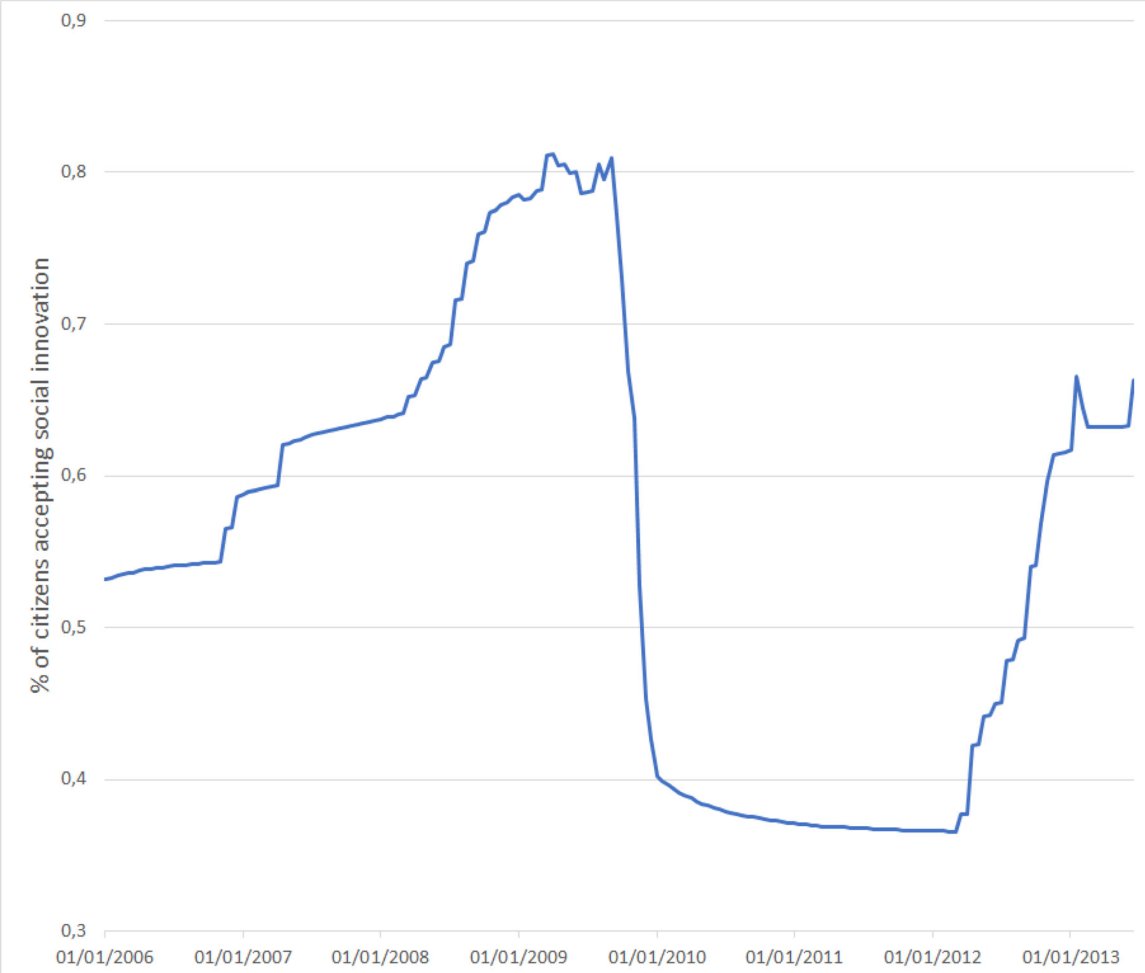


FIGURE 10 Evolution of citizen acceptance in a simulation of the real Vitoria-Gasteiz superblock project.

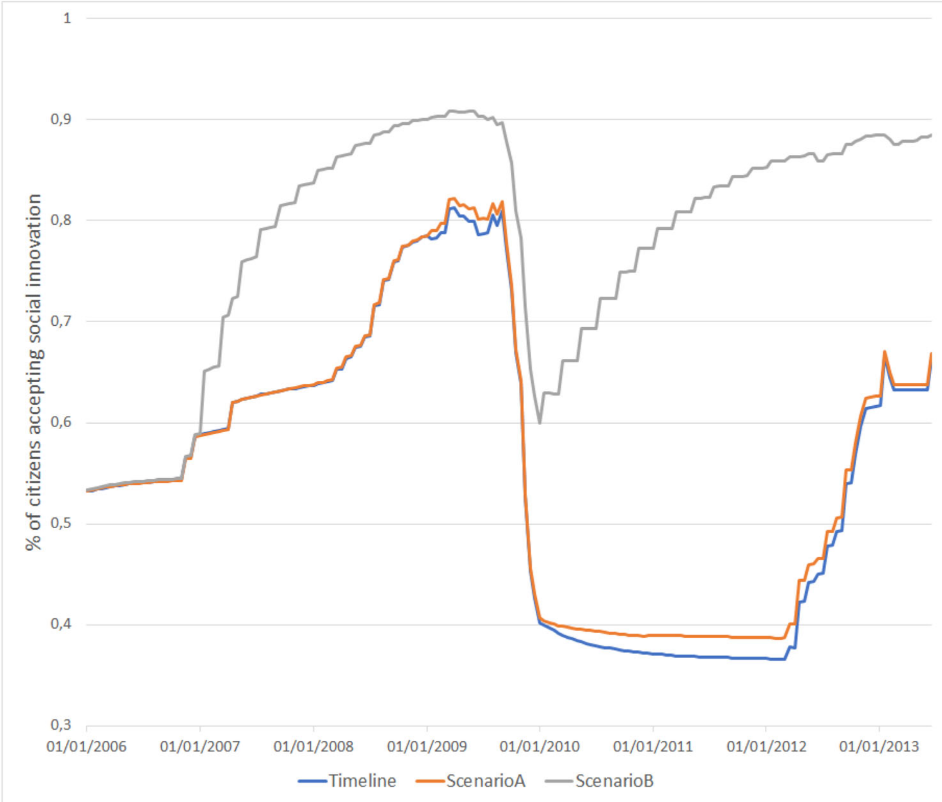
TABLE 6 New communications in alternative what-if scenarios for Vitoria-Gasteiz.

Scenario	Sender	Communications (direct/indirect)	Reach (% social network)	Period
A	City Council	18 (12/6)	Low (10)	Monthly from Jan, 2009 to June, 2010
	Associations	4 (0/4)	High (30)	Jan, April, August, Dec 2009
	Local press	3 (3/0)	High (30)	Jan, June and Dec 2009
B	City Council	13 (13/0)	Medium (20)	Bimonthly from Jan, 2007 to May, 2013
	Local press	13 (13/0)	Medium (20)	

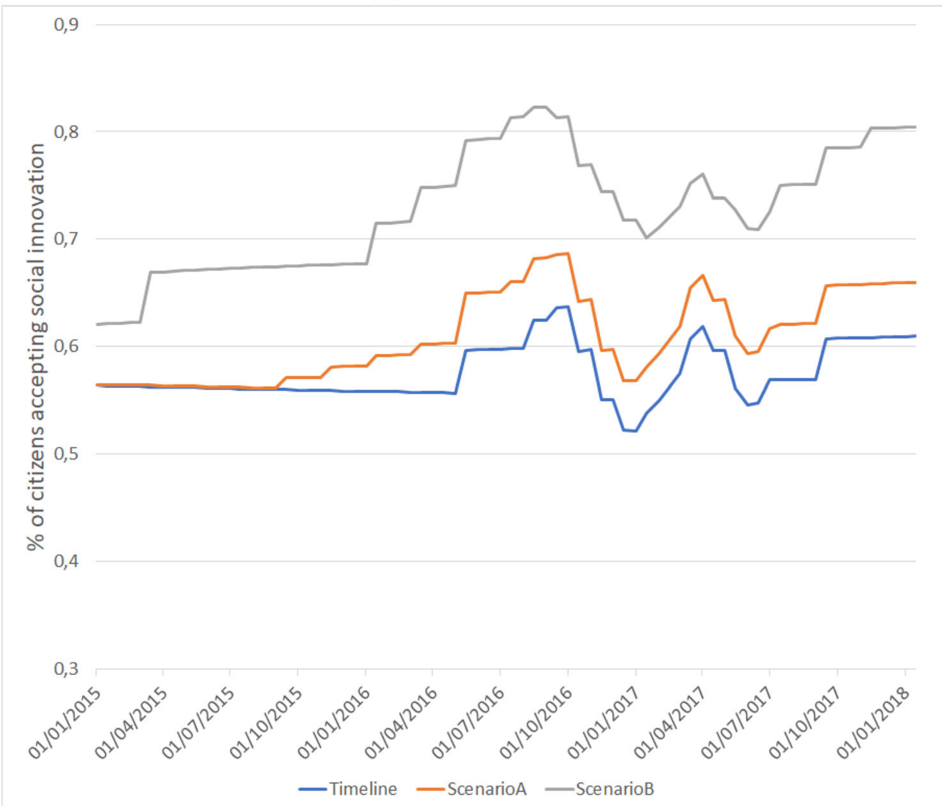
6 | A SANDBOX FOR STAKEHOLDERS: TESTING WHAT-IF SCENARIOS

The main interest of ABMs is to act as a sandbox for policymakers so that they can assess the impact of certain measures on citizen behaviour. Alternative scenarios constitute variants of a real situation where certain events, agent communications, and critical node communication plans can be modified. Simulating alternative scenarios allows policymakers to develop better actions to foster citizen acceptance of projects.

Below, we analyze alternative scenarios proposed by the sociologists and stakeholders who participated in the SMARTEES workshops (Dumitru et al., 2021, 2019), and compare their effects in the two cities in which a superblock project was modelled, that is, Vitoria-Gasteiz and Barcelona.



(a) Vitoria-Gasteiz.



(b) Barcelona.

FIGURE 11 Evolution of the acceptance of the simulations performed for alternative scenarios being a) the one for Vitoria-Gasteiz and b) the one for Barcelona. The original timeline is also shown to facilitate comparison. The *Y*-axis shows the number of citizens accepting the social innovation.

TABLE 7 New communications in alternative what-if scenarios for Barcelona.

Scenario	Sender	Communications (direct/indirect)	Reach (% social network)	Period
A, B	City Council	13 (13/0)	Medium (20)	Bimonthly from Sep, 2015 to Sep, 2017
	Local Media	13 (13/0)	Medium (20)	

TABLE 8 Final acceptability of alternative what-if scenarios.

Scenario	Vitoria-Gasteiz	Barcelona
Timeline	66.30 ± 0.32	60.90 ± 0.31
A	66.86 ± 0.32	65.95 ± 0.39
B	88.45 ± 0.25	80.41 ± 0.36

6.1 | Alternative scenarios: Enhanced communication campaigns

As mentioned, in November 2009, the acceptability of the superblock project in Vitoria-Gasteiz was seriously affected by the negative impact of a new parking policy communicated by the City Council using a rather ineffective strategy which focused overly on the benefits of sustainable mobility and superblocks and increasing environmental awareness.

We analyze an alternative scenario in which the project promoters implement a different communication strategy aimed at meeting the specific needs of residents. We simulate a scenario in which the communication campaign focuses on showing how the project would enhance not only environmental quality but also satisfy other needs of the agents in the affected neighbourhood. We propose two alternative scenarios, A and B.

Scenario A reflects a more aggressive communication campaign that anticipates the dissatisfaction of residents who feel that the new policy is inconvenient for them because it eliminates free on-street parking. Hence, the promoter's communication focuses on other aspects that would improve citizen satisfaction, such as noise reduction, more free space for public use, and so forth. Table 6 Scenario A describes the total number of communications, including whether the message was direct from the sender or indirect via the local press, and the population proportions reached. Note that all communications were dispersed equally throughout the specified time period.

Figure 11a shows that this alternative scenario results in almost the same acceptance as the real scenario, except for a slight improvement in the period of lowest acceptance (2010–2013). Hence, the new communication policy barely enhances overall acceptance with respect to the original communication, going from 66.30% to only 66.86% (see Table 8).

Scenario B (see Table 6) addresses all other relevant needs (wellness, comfort, participation, and city prestige) in the communication campaign. Figure 11a shows that this scenario increases acceptability throughout the process, smoothing the 2010 drop, and rapidly recovering acceptance during a period of minimum acceptability.

To observe how the success of one scenario or another depends on the demographic and sociopsychological characteristics of the population, the same scenarios are simulated for Barcelona, focusing on the Poblenou neighbourhood where superblock implementation was especially controversial. This new communication campaign is described in Table 7.

Figure 11b and Table 8 show that scenario A in Barcelona achieves slightly greater acceptance (by almost 6%) throughout the whole process, but does not manage to smooth the curves. Scenario B achieves greater acceptance and smooths most of the drops in acceptability, with the exception of that at the end of 2016. This would suggest that acceptance of social innovations increases when communications address key needs. Scenario B shows the highest acceptability, improving by nearly 20% compared to the original scenario. Table 8 shows that scenario A is more effective in Barcelona than in Vitoria-Gasteiz (6% vs. 0.56%), while Scenario B achieves very high levels of acceptance in both cities.

Further alternative scenario simulations are described in Dumitru et al. (2021) and Bouman et al. (2021).

7 | CONCLUSIONS AND FUTURE WORK

The described ABM is capable of simulating the evolution of citizen acceptance, citizen-to-citizen communications, and the role of relevant organizations in a social innovation process. Specifically, the model has the following characteristics:

- It uses the HUMAT decision-making model to evaluate possible behavioural alternatives of citizens.
- Using real data, it represents citizens at the individual level in terms of their needs and psychosocial characteristics and so adapts the ABM to the analysed population.

- It accounts for two social networks (friends and neighbourhoods) that influence citizen decision-making.
- It enables an evaluation of the effectiveness of communication campaigns conducted by relevant groups and institutions and focused on citizen individual needs and behaviours, and an evaluation of the effects of behavioural change on acceptance of the project.
- It is adaptable to the characteristics of any city or area undergoing a social innovation process, representing it in a 2D environment.

The model can easily be adapted to other geographical areas, as demonstrated by the two cases used in this article (Vitoria-Gasteiz and Barcelona) and even to other social innovation processes. The alternative scenarios simulated above exemplify the model's ability to represent alternative what-if scenarios. This demonstrates ABM's usefulness for stakeholders, who can test the effectiveness of their communication campaigns according to the characteristics of the target population, thus saving effort and costs.

Note that, although the virtual environment is effective in situating agents and establishing their social networks, it remains static after initial configuration and so does not reflect changes that may arise during implementation of the social innovation. It could therefore be interesting to configure a dynamic virtual environment that better represents social innovation implementation.

Evaluating behavioural alternatives computationally is linearly complex, so scaling the model should not be a problem. However, increasing the number of agents also implies increasing the number of links, evaluations, and communications; this means greater memory and time demands in simulations, which may be prohibitive for certain devices. Note, however, that, as discussed in Section 4.2, the model results are not very sensitive to the number of agents.

Finally, enhancing the intelligence and capabilities of critical nodes so that they can react to evolving acceptance levels or execute defined plans would generate more interest in alternative scenarios and allow the simulation of more complex situations.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Citizen acceptability of superblocks in Vitoria-Gasteiz, Spa at https://zenodo.org/records/5764240.

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ENDNOTES

[1] https://www.undp.org/.

[2] https://local-social-innovation.eu/.

[3] While a search in Scopus for 'urban development' and 'agent-based' yields more than 100 results, 'agent-based' and 'superblock' only retrieves three results, all related to the SMARTEES project.

[4] It refers to the idea that city dwellers can access most of their shopping, work, education, entertainment, and so forth needs within 15 min, on foot, cycling, or using other modes of transportation (e.g., bus, rail) (Chen & Crooks, 2021).

[5] Overall satisfaction levels are considered similar if there is a difference between them of less than 10%.

[6] Dissonance levels are considered similar if there is a difference of less than 10%.

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APPENDIX

ADAPTATION TO BARCELONA

Barcelona is a pioneering city in establishing superblock areas, with the first superblocks created in the Born and Gràcia districts in 1993 and 2006, respectively. Inspired by these positive experiences, in September 2016, the City Council extended the superblock model throughout the city, to respond to the scarcity of green spaces, high levels of pollution, environmental noise, accident rates, and unhealthy lifestyles. The implemented plan pursues the objectives of enhancing the habitability of public spaces, increasing urban greenery and biodiversity, and promoting low-carbon mobility. The promoters have developed a participatory process that engages representative resident and interest groups in co-designing superblock action plans. Superblocks have received social support in some areas (e.g., Sant Antoni, Horta) but also has met high levels of resistance in other areas (e.g., Poblenou), which has tended to drop off over time. Resistance was motivated by a lack of information and of social participation prior to starting interventions. For this reason, the Poblenou superblock was chosen to adapt the model.

To adapt the model to Barcelona, we followed previously defined steps:

1. The Poblenou superblock project was implemented from early 2016 to the end of 2017.
2. To obtain data on citizens, a specific survey was carried out in Poblenou.
3. Relevant needs were identified as for Vitoria-Gasteiz (see Table 5). Sociodemographic variables, modified to represent the population, were as follows: the first five coincide with those for Vitoria-Gasteiz as reflected in Table 5 (age, gender, occupation, educational level, census tract), while the remaining variables ('children?' and 'years in the neighborhood') were replaced by having/not having a business in the neighbourhood and owning/not owning a home in the neighbourhood.
4. Since the real data obtained was not enough to represent the population of Poblenou (643 completed surveys), a decision tree was trained using as output a question about the future development of a superblock and generating simulated agents (as explained in Section 4.1), depicted in Figure A1.
5. The virtual environment was created (following the procedure presented in Section 3.1.1) using data on census tracts for the Poblenou neighbourhood.
6. To represent neighbourhood networks, a value of 1 was used for the size of the circle, such that agents living in the same streets are neighbours. For the friends network, each agent was assigned a parameter to determine a minimum number of friends and relationships were established based on homophily in age and educational level.
7. The critical nodes considered relevant for adaptation of the model were as follows:
    - City Council as the main promoter of innovation
    - Local associations, some for and some against

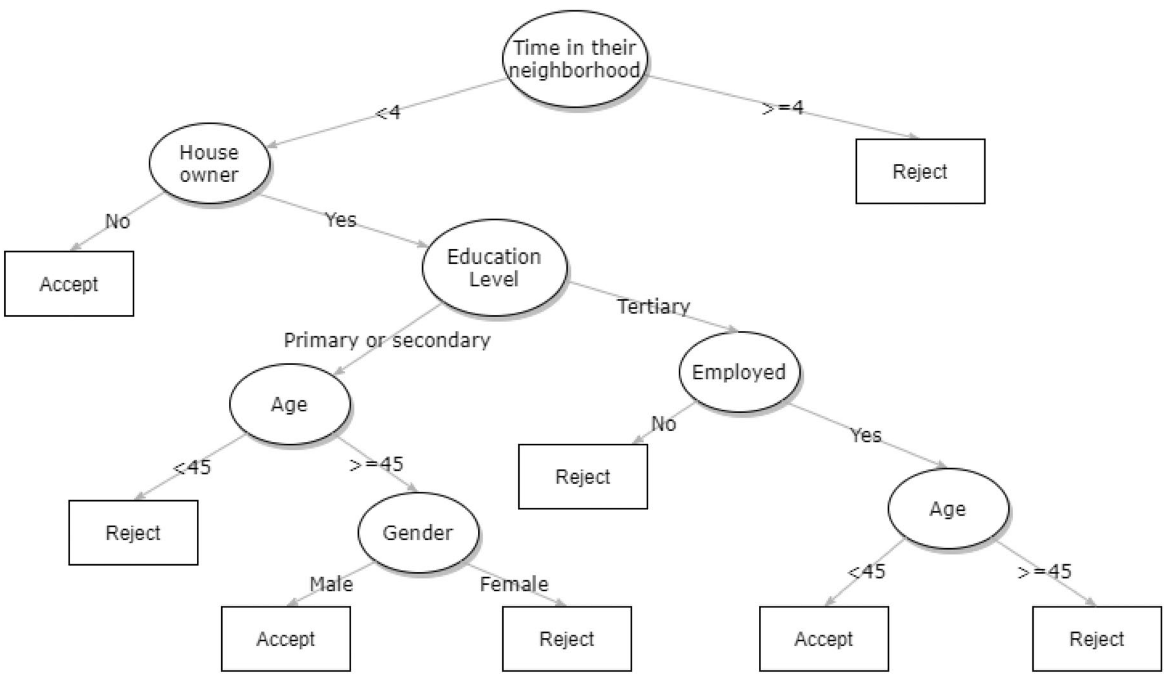

FIGURE A1 Decision tree classifying Poblenou citizens in several clusters.

- ◦ The local press, echoing the events associated with social innovation
- ◦ Political opposition, as opponents of innovation

8. To determine critical node strategies, documents and news published during the development of the project were systematically reviewed.
9. After 100 simulations with the model, the graph depicted in Figure A2 was obtained, showing the evolution of citizen acceptance during the project. Acceptability was low around October 2016, corresponding to social resistance, but started to increase with final project implementation in March 2017, although with a slight dip in this last phase.
10. The simulations were presented in workshops with representation from the different agents involved in the superblock project, and the model was calibrated and then validated by experts.

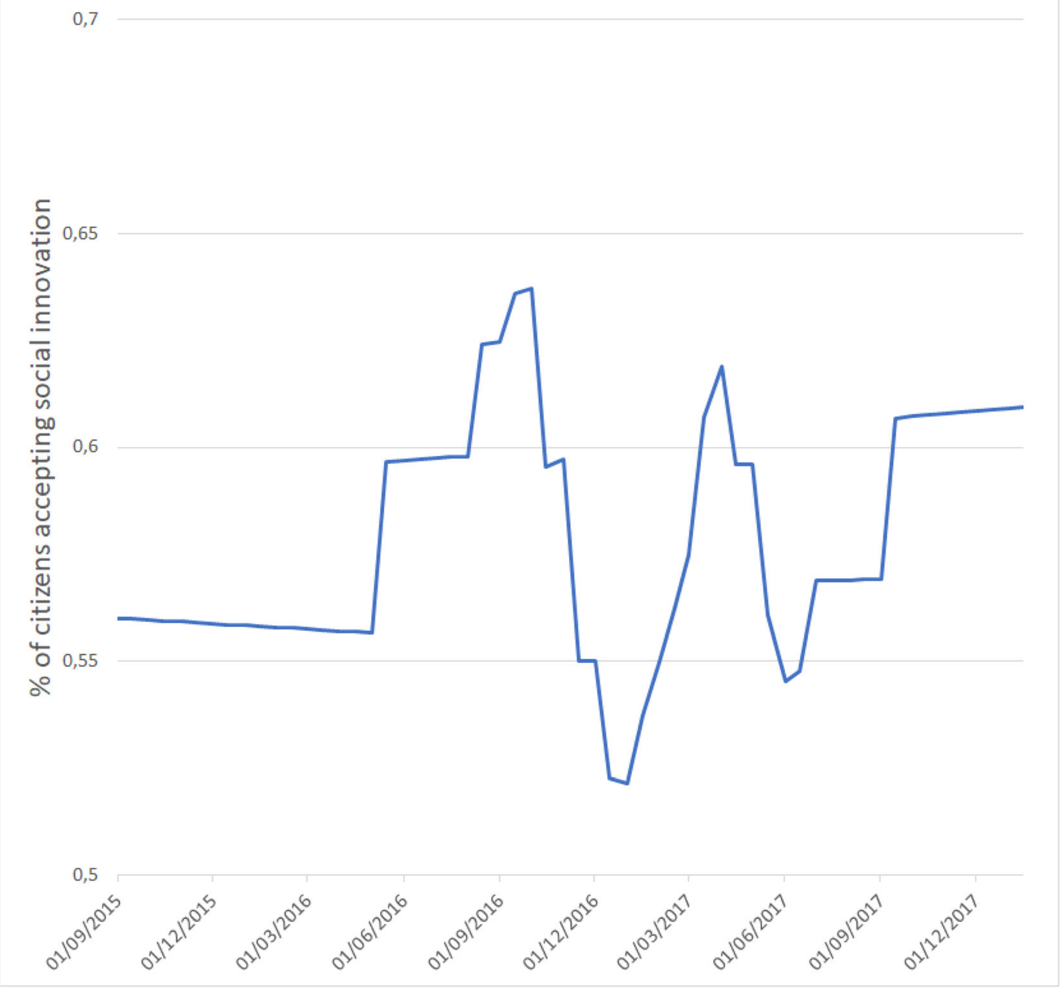

FIGURE A2 Evolution of acceptance in the simulation of the real case of Poblenou. The *Y*-axis shows the number of citizens accepting social innovation.