Preprint – IJCAI 2025: This is the accepted version made available for conference attendees.
Do not cite. The final version will appear in the IJCAI 2025 proceedings.

Agent-based Modeling Meets the Capability Approach for Human Development: Simulating Homelessness Policy-making

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Abstract

The global rise in homelessness calls for urgent and alternative policy solutions. Non-profits and governmental organizations alert about the many challenges faced by people experiencing homelessness (PEH), which include not only the lack of shelter but also the lack of opportunities for personal development. In this context, the capability approach (CA), which underpins the United Nations Sustainable Development Goals (SDGs), provides a comprehensive framework to assess inequity in terms of real opportunities. This paper explores how the CA can be combined with agent-based modeling and reinforcement learning. The goals are: (1) implementing the CA as a Markov Decision Process (MDP), (2) building on such MDP to develop a rich decision-making model that accounts for more complex motivators of behavior, such as values and needs, and (3) developing an agent-based simulation framework that allows to assess alternative policies aiming to expand or restore people's capabilities. The framework is developed in a real case study of health inequity and homelessness, working in collaboration with stakeholders, non-profits and domain experts. The ultimate goal of the project is to develop a novel agent-based simulation framework, rooted in the CA, which can be replicated in a diversity of social contexts to assess policies in a non-invasive way.

1 Introduction

According to a recent report by the Organization for Economic Cooperation and Development (OECD), approximately 2.2 million people experience homelessness in its 35 member countries [OECD, 2024]. In the European Union, it is estimated that on any given night, at least 895,000 people sleep on the streets [FEANTSA and Abbé Pierre Foundation, 2023]. In Barcelona, Spain, the number of people sleeping rough increased from 658 in 2008 to 1,063 in 2022 [Xarxa d'Atenció a Persones Sense Llar (XAPSLL), 2023]. Similar trends are observed in London and San Francisco, where the number of people experiencing homelessness (PEH) has tripled and quadrupled [Trust for London, 2023; City and County of San Francisco, 2024].

The increasing scale of homelessness demands for urgent and alternative policy-making. European institutions have called for a shift from traditional homelessness management to a model that aims to actually solve this complex social challenge by offering comprehensive support to PEH [European Commission, 2021]. This aligns with the Universal Declaration of Human Rights [United Nations, 1948] and the Capability Approach (CA), which underpins the United Nations Sustainable Development Goals (SDGs) [Gasper, 2017]. Unlike traditional development models, which focus on the amount of resources available to individuals (e.g. utilitarian frameworks), the CA shifts the attention to the people's ability to transform these resources into opportunities or capabilities (what people are actually able to do and be). From this perspective, homelessness and poverty can be understood as severe forms of capability deprivation [Marshall, 2024], where individuals are unable to access their central capabilities (in Table 1). Central capabilities are a list of ten 'essential human entitlements to be able to conduct a meaningful life with dignity' [Nussbaum, 2011], such as being able to be adequately nourished or sheltered, being secured against violent assault, or being able to undertake employment. Providing the required support to PEH requires not only the provision of material resources (food or shelter), but also social and institutional arrangements aiming to restore and expand these central capabilities [Sen, 1999].

Non-profit and governmental organizations are responding to this social challenge with transformative policy proposals. For instance, in Barcelona, the "Proposed Law on Transitional and Urgent Measures to Address Homelessness" [Sant Joan de Déu Serveis Socials Barcelona, 2023] is currently under discussion. So we are collaborating with domain experts and non-profit organizations (namely Arrels Fundació, Caritas and Salut Sense Llar), as well as with human development academics specialized in poverty (namely from the The Sustainability, Economics and Ethics (SEE) group). Our research aims to provide empirical results that guide the evaluation and implementation of these novel policy approaches.

To achieve this, we propose building a novel social simulation tool rooted in the CA. This is an innovative and interdisciplinary project, which draws on expertise from human development and computer science to explore the applica-

Life	Being able to live to the end of one's lifespan without premature death
Bodily health	Being in good physical health, including reproductive health
Bodily integrity	Being able to move freely, being free from violence, having bodily, reproductive, and sexual autonomy
Senses, imagination, thought	Being able to reason, think, and create; having access to art, literature, and science; and enjoying pleasurable experiences while avoiding non-beneficial pain
Emotions	Being able to form and mourn emotional attachments to others
Practical reason	Being able to conceptualize what is good and plan one's future
Affiliation	Subdivided into interactions with others and dignified, non-discriminatory participation in society
Other species	Being able to live with concern for animals, plants, and the natural world
Play	Laughter, play, and recreational activities
Control over one's environment	Subdivided into political participation and material rights to own property and undertake employment

Table 1: Central Capabilities, adapted from [Nussbaum, 2011].

tion of the CA in the agent-based modeling (ABM) and reinforcement learning domain. Additionally, we integrate complex motivators of behavior, such as human values [Schwartz, 1992] and needs, into the CA. This seeks to enhance the modeling of human behavior in the context of homelessness and contribute to prior research into the computational representation of human values [Osman and d'Inverno, 2024].

The goals of the project are as follows:

1) Implement the framework of the CA as a Markov Decision Process (MDP) that can be applied across social contexts where inequity arises, such as homelessness.
2) Building on such MDP, develop a novel and rich agent decision-making model that accounts for complex motivators of behavior, including human values and needs.
3) Develop an agent-based simulation framework to assess the impact of policies on people's capabilities and identify those that effectively restore or expand them, working towards the UN SDGs.

Our project will leverage agent-based modeling (ABM), which in the context of homelessness, allows to simulate the behavior of a diversity of stakeholders involved (including PEH, social workers and non-profits), interacting with each other autonomously. ABM will facilitate (1) the exploration of outcomes through both top-down (impact of legal policies) and bottom-up (impact of resources or disparities) processes, (2) the modeling of individual behavior, social interactions and the role of policies in restoring their central capabilities and (3) the evaluation of both of the above from the perspective of equity [Williams *et al.*, 2022]. In this paper, we define equity and inequity in terms of having (or lacking) basic capabilities [Sen, 1979] to conduct a meaningful life with dignity [Sen, 1999], in line with the CA. We acknowledge complementary interpretations of inequity, on the basis of distribution of income and wealth [Piketty, 2017], oppression and social justice [Sen, 1979], the equality of opportunities and meritocracy [Sandel, 2020], social and political recognition [Honneth, 1996; Taylor, 1989], or the representation in political and economic institutions [Acemoglu and Robinson, 2012], among others.

2 Related Work

2.1 The Capability Approach

The capability approach (CA), originally developed by Amartya Sen [Sen, 1999] and further expanded by Martha Nussbaum [Nussbaum, 2011], is a flexible and multi-purpose framework for analyzing how to promote and assess human well-being, development, and social justice. Rather than looking only at resources or outcomes (functionings), it focuses on the opportunities (capabilities) people have to lead the lives they value. Following [Robeyns, 2017] terminology we define the key terms for computational purposes, illustrated in black in Fig. 1:

1. **Resources**: set of commodities and services that are available to a person in a given context, such as a bike, adequate shelter, or public healthcare.
2. **Conversion Factors**: Characteristics that facilitate the transformation of resources into capabilities. These include personal (such as physical condition, reading skills or gender), social (such as social norms, public policies or discrimination) and environmental (such as climate, infrastructures or transportation).

   In our work, social conversion factors will be interpreted as social and legal norms in line with social laws in [Shoham and Tennenholtz, 1995]. We highlight that these norms could also serve as proxies for institutional discrimination [Aguilera *et al.*, 2024].
3. **Capabilities**: what people are able to do and be given their resources and conversion factors. In our work, it will be useful to distinguish between the following:
   (a) **Central capabilities:** Ten basic capabilities that everyone should be entitled to as a matter of human dignity [Nussbaum, 2011], defined in Table 1.
   (b) **Specific capabilities:** Context-dependent capabilities. For instance, 'being able to move from a peripheral neighbourhood to work' can be considered the more specific capability for 'being able to move freely from place to place', related to the central capability of *bodily integrity* in Table 1.

In line with [Robeyns, 2017], central capabilities will be the ends of policy-making and part of the evaluative space for assessing inequity in our work. Specific capabilities will be the contextual ends or goals of individuals, represented as possible actions, and often serving as means for enabling central capabilities. This follows the means-ends distinction in the CA, which differentiates between capabilities as ends or as means to achieve other ends. The idea is that by acting upon specific capabilities (realising actions), individuals can restore central ones, because capabilities are interconnected: achieving one can enable others (both for an individual's own development or a society's development).

4. **Choice Factors**: Motivators of behavior influencing the indidivual's choice of acting upon specific capabilities (preferring to perform one action over another).

   > *"There is very little about these constraints that one could say in general terms, as they are so closely interwoven with a person's own history and thus with her personality, emotions, values, desires and preferences."* [Robeyns, 2005]

   Given the underspecified role of choice factors in the CA literature, our work incorporates individual needs and values into the framework, drawing on context-specific sources and established theories, such as Schwartz's value framework [Schwartz, 1992].

5. **Functionings**: Realized actions, what people end up doing and being in practice.

In the context of inequity, poverty and homelessness, it makes sense to define behavior not only in terms of *what people value or need to do and be*, but also in terms of *what people can actually do and be*. The capability approach addresses these fundamental questions: what are people actually able to do and be, given their circumstances? And how individual capabilities can be expanded so that all human beings can conduct a meaningful life with dignity? It emphasizes that our action space is constrained by resources and conversion factors, i.e. there are things we cannot do because we lack the means or the personal, social and environmental circumstances to do them. Capabilities provide this counterfactual information that is normally overlooked in computational decision-making architectures: they represent the set of an individual's impossible and possible actions to be realized. The choice of which possible action we realise in a particular instant of time (which capability is transformed into a functioning), depends on individual goals and motivators of behavior (personal choice factors).

2.2 The CA in Agent-based Modeling

There is an important body of ABM literature focusing on equality, equity and fairness in different practical domains. However, to the best of our knowledge, few publications in the agent-based modeling literature use the capability approach as a conceptual framework for social simulation. The existing literature that does, can be broadly divided into two research lines: (i) using ABMs as a tool to infer capabilities for CA purposes, and (ii) using the CA as a conceptual framework for designing ABMs.

The first line of research is a very small body of work that combines ABM with Structural Equation Modeling (SEM) [Chávez-Juárez and Krishnakumar, 2021]. Although related, their main purpose and methods are not aligned with our research. The second line of research involves creating ABMs for practical domains, such as in energy justice [Melin *et al.*, 2021; Assa and Lengfelder, 2020; De Wildt *et al.*, 2020] and community resilience [Markhvida *et al.*, 2020; Silva-Lopez *et al.*, 2022; Tseng and Stojadinović, 2024]. These studies mainly examine how capabilities and functionings (in the evaluative space) are affected by different resources or conversion factors. While in [Tseng and Stojadinović, 2024] the simulation is rooted in the CA (as we intend to do), their choice factor is entirely dependent on [Maslow, 1943]'s hierarchy of needs. This may be suitable for their context, but we consider it oversimplifies the CA's core principle, which underscores that all capabilities are essential and does not prescribe a universal hierarchy of prioritization.

Our framework aims to address this gap by including more complex motivators of behavior in the choice factor, such as value and need preferences, informed by context-specific data. This aims to provide a robust decision-making that can be applied across contexts where inequity arises. We emphasize the need for interdisciplinary collaboration to define all relevant aspects of the approach by following [Robeyns, 2017]'s modular view of the CA. We work towards its operationalization in the computational domain, using an MDP as the technical basis of the decision-making.

3 Methods

Before presenting our proposal, we begin with an example that highlights our motivation and objective. From there, we explain: 1) how the CA and its notions, such as conversion factors, capabilities or choice factors (including values and needs) can be implemented computationally, 2) how can we develop a novel and rich agent decision-making model by mapping the CA to an MDP; and 3) how to develop an agent-based simulation framework that allows us to evaluate the impact of policies aiming to expand or restore people's capabilities, in line with the UN SDGs.

3.1 Example: The Difference a Bike Makes

Let's consider a simple and practical example in the CA framework: a person with access to a bike. A bike, in general, should provide a person with the ability to move freely and faster than walking. However, the person's ability to ride a bike is not only dictated by available resources, but by several conversion factors that vary from one person and context to another. For instance, (i) if the individual has a disability or doesn't know how to ride a bicycle (personal factors), (ii) if riding a bicycle is forbidden or discouraged by social or legal norms (social factors), or (iii) if the individual lives in a snowy place that renders riding a bike impossible (environmental factors). Conversion factors help us define the probability of a capability being enabled from available resources. This probability can either be binary, completely conditioning whether a person moves or not with 100% or 0% probabilities, or non-binary, partially conditioning a person's mobility.

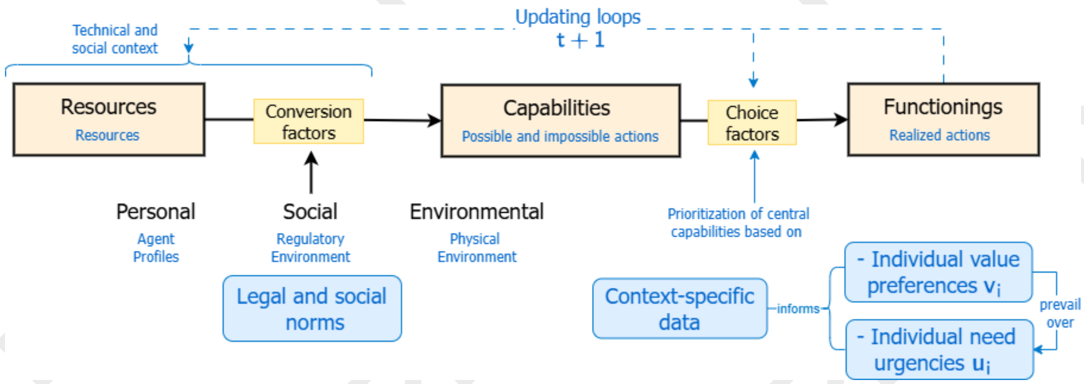

Figure 1: Schematic overview of the Capability Approach [Robeyns, 2017] (in black and warm tones), with the integration of computational elements to operationalize it in the agent-based modeling domain (in blue).

Note that if ‘riding a bike’ is a possible action, choosing to perform that action may act as a mean for enabling other actions, such as ‘securing a job’. All these actions can be related to central capabilities, such as *bodily integrity* or *control over one’s environment* in Table 1. In this way, possible actions can serve as evaluation criteria to assess central capabilities.

Choosing to realise an action is driven by personal choice factors, such as values and needs. For instance, in situation (ii), where riding a bicycle is discouraged by our society, a strong alignment with *tradition* and *conformity* values may lead a person to prefer walking over biking, even if walking takes significantly more time. On the other hand, someone valuing *stimulation* over *tradition* may choose to bike, despite social and legal norms or (iii) hazardous snowy conditions, simply for the thrill and adventure. Our framework aims to build the decision-making taking such personal choice factors into account.

3.2 Proposed Choice Factors for an Enhanced Decision-Making Model

Different motivators of behaviors have been considered in the literature. Values, according to [Schwartz, 2012], “refer to desirable goals that motivate action”. Needs, as defined by [Maslow, 1943], have also been considered as basic motivators of action. Their connection to values has been previously established. For instance, in [Dignum, 2021], the authors recognize that values inform the prioritization of needs, but behavior is primarily driven by Maslow’s needs.

Proposed Choice Factors. In our work, needs give an indication of *urgency* and values give an indication of *importance* to our actions or goals. We differentiate between urgency-based actions (or short-term goals), that we perform for the short-term reward, and importance-based actions (or long-term goals) performed for the long-term reward. For instance, in the context of homelessness, a person might urgently seek shelter (urgency-based action), yet choose to remain disengaged from social services (importance-based action). Although accessing shelter could provide immediate short-term rewards, a strong alignment with certain values, such as *security*, may prevail over the need, prioritizing long-term rewards instead. We treat values as prevailing over needs, although the detailed interactions between them will be explored in our proposed work.

Capturing individuals’ value preferences and need urgencies is usually a complex task. One way to address this challenge would be to rely on questionnaires with the PEH to understand their priorities in a given context (e.g. in terms of the central capabilities in Table 1). This information, corresponding to ‘context-specific data’ in Fig. 1, could then be used as the baseline for modeling individual variations in the choice factor when initialising the agent population. Overall, as can be seen in Fig. 1, our work considers that legal and social norms [Shoham and Tennenholtz, 1995] form the social conversion factors (from resources to capabilities). Also, we consider that context-specific data informs individual need urgencies and value preferences [Schwartz, 1992], which act as choice factors (from capabilities to functionings).

Implementation. From a computational perspective, we talk about possible, impossible and realized actions or goals, tied to short and long-term rewards. Possible (and impossible) actions represent capabilities (and deprived capabilities), whereas realized actions are the functionings in the CA literature. Short and long-term rewards represent the choice factors (need urgencies and value preferences) driving an agent’s decision-making process. Actions seeking short-term rewards are driven by need urgencies, while actions seeking long-term rewards are driven by value preferences. The latter set of actions often enables the restoration of central capabilities (e.g. ‘securing a job’ is an action seeking long-term rewards that enables *control over one’s environment* in Table 1). Additionally, when we consider the dynamics of the decision-making, i.e., how the realized actions influence both the individual and overall system over time, two fundamental updating loops appear, represented in Fig. 1:

1) **The impact of realized actions on resources and conversion factors**. Realized actions lead to updates on the agents’ states. For instance, ‘riding a bike’ might help me achieve the necessary conditions to ‘secure a job’. We build on [Tseng and Stojadinović, 2024] approach to take into consideration this updating between agents’ behavior and what they call technical and social context, which includes resources and conversion factors.

Concept	**Capability Approach**	**Markov Decision Process**
Input and output	Resources, Personal characteristics, Need and value preferences	States
From resources to capabilities	Conversion Factors	Transition Probabilities
From capabilities to functionings	Choice Factors (need urgencies and value preferences)	Short and Long-term Rewards
Behavior	• Specific capabilities • Deprived specific capabilities • Specific functionings	• Possible actions • Impossible actions • Realized actions
Output	Central capabilities and functionings	Long-term goals

Table 2: Mapping between the Capability Approach and a Markov Decision Process.

2) **The impact of realized actions on choice factors**. Realized actions might also result in updating choice factors. For example, if I 'have an accident while riding a bike' because I was careless, I might become more cautious next time. This implies that my preference for being healthy has increased, influencing the rewards functions of the decision-making.

3.3 The Capability Approach as a Markov Decision Process

In reinforcement learning, the Markov decision process (MDP) framework defines the interaction between a learning agent and its environment using states, actions, transition probabilities, and rewards. By mapping CA concepts in Fig. 1 to MDP elements in Table 2, we enable the use of reinforcement learning to model the agents' decision-making.

- State s represents the current situation the agent is in. In our framework, this includes almost all the information: the agent's personal characteristics, the available resources, and the individual need and value preferences.
- Actions are the set of possible decisions a that the agent can make to interact with its environment. In our framework, we differentiate between possible, impossible and realized actions, analogous to specific capabilities, deprived capabilities and functionings.
- Transition probabilities $P(s'|s,a)$ are the probabilities of moving from one state s to another state s' after taking action a. In our framework, transition probabilities may be used to represent conversion factors, or the probability of being capable of performing an action. One can imagine, for example, that impossible actions would have associated a 100% chance of remaining in the same state, representing that nothing is happening.
- Rewards are the feedback the agent receives when choosing action a in a given state s. In our framework, this is how much have the choice factors (value preferences and need urgencies) been satisfied by that action. We differentiate between short-term and long-term sums of expected rewards, $Q_s(s,a')$ and $Q_l(s,a')$, to reflect urgency-based and importance-based outcomes.

One main objective of our research is to study how these expected rewards are defined. For that, we need to analyse the dynamics between need urgencies and value preferences. The agent's policy $\pi(a|s)$ will define the probability of selecting action a in state s based on these two types of expected rewards

$$\pi(a \mid s) = \begin{cases} 1, & \text{if } a = \arg\max_{a'} \oplus(Q_s(s,a'), Q_l(s,a')) \\ 0 & \text{otherwise,} \end{cases}$$

where $\oplus$ indicates an aggregation of short-term and long-term reward components.

The novelty of the decision-making would precisely be defining this aggregation of needs and values for driving behavior. Of course, different discount factors $\gamma \in [0,1]$ will need to be considered for the different reward types. This will allow to account for short-term and long-term effects of the agent's actions with lower or higher values of the discount factor, respectively. Depending on the results, we may also consider introducing constraints to specify that needs are addressed as long as they do not conflict with values.

3.4 Towards Assessing Policies in terms of Capabilities with Agent-based Simulations

The defined MDP will be the basis of the decision-making in the agent-based simulation. This simulation will allow to assess the impact of policies through the lens of capabilities. Building upon [Aguilera *et al.*, 2024], the simulation will be composed by (1) agents' profiles, (2) a physical environment and (3) a regulatory environment. By simulating agents' profiles, including personal conversion and choice factors instantiated from real-worl data, we will obtain a representation of the stakeholders involved, such as PEH, healthcare and social services, and non-profit organizations. The MDP will define their behavior and social interactions based on these profiles. The physical and regulatory environment will determine their surroundings, including resources, social, and environmental conversion factors. In particular, legal norms will affect the agents' state and actions. The impact of such policies will be assessed by analyzing each individual's set of possible and impossible actions (enabling restored and deprived central capabilities) among other elements discussed in Section 5.

4 Foreseen Case Study

Our proposed case study examines healthcare challenges in Barcelona's Raval neighbourhood, where the majority of PEH are located. According to *Salut Sense Llar*, an organization of doctors specialized in treating PEH, the main problems they face include a systemic exclusion from primary healthcare (PHC), pharmaceutical poverty and a lack of post-discharge assistance [Saumell *et al.*, 2024]. Despite suffering from lower life expectancy and higher morbidity [Lahiguera *et al.*, 2022], PEH encounter major barriers to accessing social and healthcare services. For instance, those in irregular administrative situations (non-registered citizens) are unable to access PHC. As a result, their health worsens over time, often reaching a critical point where they require emergency care and hospitalization.

Several studies show that integrating PHC in the management of PEH improved the diagnosis and treatment of chronic diseases while reducing visits to emergency services and hospital admissions [Joyce and Limbos, 2009; O'Toole, 2010; Ponka and Agbata, 2020]. Motivated by this evidence, the legal policies proposed by *Salut Sense Llar* aim to address these health inequities, leading to personal suffering and both ethical and economic costs to society more broadly. Their goal is to offer improved healthcare to PEH by guaranteeing an inclusive PHC, with multidisciplinary teams, attention in situ, and a gender-sensitive approach.

Roybens' modular view of the CA provides a robust lens to capture the healthcare challenges suffered by PEH. We start with a small-scale example, while acknowledging that its complexity should be enhanced for the use case to be truly informative. To begin with, we should consider multiple (if not all) central capabilities in Table 1 both in the rewards and the evaluative basis of the simulation. However, we begin by targeting *bodily health* to show how the case study can later be developed within the project.

4.1 Health Inequity as a CA-based MDP

We focus on two scenarios: a sick registered citizen (A) and a sick non-registered citizen (B). The difference lies in how a legal norm constrains their access to primary healthcare (PHC). Figure 2 illustrates how the situation can be modeled as an MDP. We make three main assumptions:

1) We assume a reduced action and state space: the only relevant information in the agents' personal profile is their health and registration state, and the only executable actions are 'receive medical attention' and 'keep forward without medical attention'.
2) We assume that transition probabilities are binary: receiving medical attention unequivocally improves the agent's health state, and the legal norm unequivocally determines whether the agent receives medical attention or not.
3) We assume simplified reward functions: we consider the agent highly values *bodily health*, enabled by the action 'receive medical attention'. We do not consider urgency-based actions or other central capabilities that could be enabled by the action 'keep forward without medical attention'.

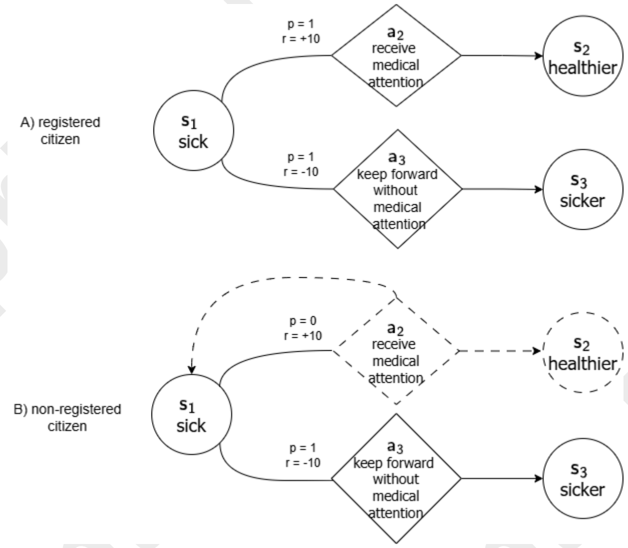

Figure 2: A Markov Decision Process (MDP) representation of the decision-making. Nodes represent states, while diamonds indicate actions that may be possible or impossible (i.e., capabilities or deprived capabilities) with lines and dashed lines, respectively.

And we consider the following elements:

1. Resources: primary healthcare (PHC) services.
2. Conversion factors / Transition Probabilities defining the possibility of actions:
   (a) Personal: health and registration state.
   (b) Social: legal norm specifying who gets access to PHC based on registration state.
3. Capabilities defining what someone can do and be:
   (a) Specific capabilities / Possible actions: being able to receive medical attention or not.
   (b) Central capabilities to be restored / Long-term goals: Bodily health.
4. Choice factors / Rewards dictating decision-making:
   (a) Value preferences: 'I value being healthy'.
   (b) Need urgencies: 'I am in pain'.
5. Functioning / Realized action: receive medical attention or not.

Under these assumptions, the MDP starts with the agent in a sick state, s_1. For a registered citizen, two actions are possible: (i) a_2 'receive medical attention' leads to a healthier state s_2 with reward $r = +10$, and (ii) a_3 'keep forward without medical attention' leads to a sicker state s_3 with reward $r = -10$. Both transitions occur with probabilities $p = 1$, meaning that the actions will unequivocally lead the agent to the associated state. Because the agent highly values *bodily health*, action a_2 is prioritised over action a_3 and the optimal policy of the agent will make him end up in a healthier state s_2. For a non-registered citizen, a_2 is an impossible action (deprived capability), although it is a highly valued goal with reward $r = +10$. The only possible action is a_3 which leads to a sicker state s_3 with negative reward $r = -10$.

4.2 Practical Implementation

The presented MDP demonstrates how can we model behavior being affected by policies that lead to inequitable health outcomes. To move beyond this proof-of-concept model, this project aims to define in detail the rest of the relevant elements listed in Section 4.1 by working closely with the stakeholders involved in this context. We will define a map environment where agents can navigate to 'succeed' or 'fail' in restoring their central capabilities and functionings based on the available resources, legal norms, etc. In order to evaluate it, we will check the action space: possible, impossible and realized actions enabling central capabilities in Table. 1, among other information (explained in Section 5) stored in the state space. For the model's input data, we will rely on existing anonymised survey data collected annually by nonprofits [Arrels Fundació, 2023] to simulate the agent profiles. By applying a probabilistic approach similar to [Aguilera *et al.*, 2025], we will sample a synthetic population from this data with additional information about the health, education or administrative state we might find relevant. Additionally, choice factors will be informed by context-specific data to guide the prioritization of central capabilities. For instance, we will use prioritizations based on needs expressed by PEH in [World Bank, 2000], and interviews from [Cáritas, 2021]. Such information can help us tune the individual variations in the choice factor, ensuring the agent's behavior aligns with lived experiencies and priorities of PEH.

5 Implementation Plans, Evaluation and Expected Social Impact

Our implementation plan begins with the development of the MDP for the health inequity use case. We will start small with the example, and then build the complexity of the model as we progress. This will give us time to address challenges in obtaining all the data we need (for example, the necessary data and procedures to obtain representative profiles of PEH, mentioned in subsection 4.2), as well as challenges in modeling (for example, defining the interactions between needs and values within the decision-making process of the agent). All this work will be carried out in close collaboration with selected nonprofit organizations and other domain experts in human development studies and PEH's healthcare. It will be of utmost importance to present to them our model's mechanism and results (in focus groups), to collect feedback that guides our work on enhancing the model's complexity.

As outlined by the CA, capabilities and functionings are essential but not exclusive elements of evaluation. To assess the simulation outcomes, we consider other indicators that help us reflect the multidimensions of homelessness: (1) the housing state (following ETHOS [Amore *et al.*, 2011] terminology), (2) the health state (establishing a quantitative scale with the pathologies described in [Saumell *et al.*, 2024]), and (3) the registration state (registered, non-registered or in process, following the descriptions of social services workers). Additionally, we will evaluate (4) governmental economic expenses for both healthcare and social services, as well as (5) discrimination within institutional frameworks, together with values being promoted or demoted by legal and social norms.

The evaluation criteria defined aligns with the multidimensionality of the CA. It is also aligned with the LNOB principle, which underscores that discrimination and inequalities (often multiple and intersecting) undermine the agency of people as holders of rights [UNSDG, 2023]. The expected simulation results would impact multiple SDGs: No Poverty (1), Zero Hunger (2), Good Health and Well-Being (3), Decent Work and Economic Growth (8) Industry Innovation and Infrastructure (9), Sustainable Cities and Communities (11), and Partnerships (17) [United Nations, 2023].

6 Challenges, Limitations and Ethical Considerations

As demonstrated through our work, the CA can be used in many different directions but needs additional specifications to become effective [Robeyns, 2017]. This makes it particularly suitable for computational modeling. However, it heavily relies on interdisciplinary collaboration to define the context-specific elements of the CA depending on the case study. For that, we emphasize the importance of following Roybens' modular view of the CA [Robeyns, 2017]. These modules include mandatory specification of key elements in the CA (conversion factors, capabilities and functionings, other dimensions of evaluative value, etc.), as well as accounts for human diversity, agency, and structural constraints. Given the need for context-specific detail, our framework will be designed to be flexible yet general enough to be applied in diverse settings where inequities arise.

As we enhance the complexity of our model, including larger state and action spaces or bigger population, scalability becomes a significant challenge. A simple MDP approach can struggle with exponential growth in states and actions, especially when considering impossible actions too (i.e., deprived capabilities). To address these computational limitations, our work will employ Q-learning and, eventually, Deep Q-Learning applied to multi-agent settings [Albrecht *et al.*, 2024], to efficiently solve the MDP within a partially observable environment (closer to real-life scenarios). This will be combined with parallelization techniques on the Ars manga cluster [Artificial Intelligence Research Institute (IIIA-CSIC), 2025] to maintain economic and energetic sustainability.

From an ethical standpoint, we plan to rely on anonymized and synthetic secondary data, ensuring privacy and confidentiality. Additionally, we emphasize the relevance of discrimination in our framework. In line with the principle of LNOB, we acknowledge that many barriers to accessing services, resources and equal opportunities are not simply a lack of availability of resources, but rather the result of discriminatory laws, policies and social practices that leave particular groups of people further and further behind [UNSDG, 2023]. Our entire proposal is focused on addressing these challenges. We will pay particular attention to aporophobia (fear or rejection towards the poor) [Cortina, 2017] and its impact throughout our research. If needed, we also plan to seek the approval from CSIC's ethics committee.

Acknowledgments

This research has been supported by the EU-funded VALAWAI (# 101070930), the Spanish-funded VAE (# TED2021-131295B-C31) and the Rhymas (# PID2020-113594RB-100) projects. Special thanks to all the local stakeholders involved: Beatriz Férnandez (Fundació Arrels) for sharing her law proposal, and Beatriu Bilbeny (Salut-sensellar) for guiding us toward identifying the key issues to address. Thanks to Núria Ferran and Bet Bàrbara, for clarifying the functioning of social services and city hall administration in Barcelona. And thanks to the human development community, including Flavio Comin and Mark Fabian, for giving us the necessary feedback to carry on with the proposal.

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