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Rabia Aziza[a,*], Amel Borgi[a], Hayfa Zgaya[b], Benjamin Guinhouya[b]

[a] *Université de Tunis El Manar, Laboratoire LIPAH, LR 11ES14, El Manar 2092, Tunisie*
[b] *Université de Lille, Laboratoire de Santé Publique, EA 2694 : Epidémiologie et Qualité de soins, 42 rue Ambroise Paré 59120, France*

Abstract

This paper aims to test and illustrate the utility and extensibility of an existing model, SimNCD (Simulation of NonCommunicable Diseases). It also proposes a way to include questionnaires - widely used in epidemiology - in the individual's reasoning mechanism in order to identify his/her attitude and personal choices.

SimNCD is a formal agent-based model. It helps researchers and health practitioners study and simulate the complex dynamics of noncommunicable diseases. It models individuals that evolve within a social network, and behave while engaging in activities offered by their physical environment. The literature strongly supports the influence of the individual's behavioral choices on their health, particularly, the acquirement and maintainability of noncommunicable diseases. Therefore, we propose to extend SimNCD in order to acquire the agents with a reasoning process that allows them to choose the activities to practice. Thus, we model their attitude via preferences that are modeled based on the available literature and expressed with the linguistic 2-tuple method. Our solution also employs a multi-attribute decision-making method. We specify the proposed solution in the study of childhood obesity and use it to predict children's corpulence variations in different scenarios.

Keywords: Agent-based modeling, decision-making, linguistic 2-tuple, noncommunicable diseases, childhood obesity.

1. Introduction

Simulation is widely used in public health, more specifically, the study of NonCommunicable Diseases (*NCDs*). The risk factors that maintain and lead to NCDs are complex and dynamic, e.g. social support, physical activity, tobacco use, and neighborhood safety. They stem from different dimensions of a person's life, e.g. social network, physical environment, and psychological level. They can influence each other and may lead to developing other diseases within the same person, which complicates their understanding and control. Nevertheless, public health researchers and practitioners believe these diseases are preventable if the right factors were targeted [1, 2, 3].

Agent-Based Models (*ABMs*) represent autonomous, independent agents that evolve within social and physical environments. This paradigm is known to better suit representing complex and nonlinear dynamics. Therefore, it is often used to model NCDs [4, 5, 6, 7, 8], like the study of the effect of transport infrastructure on walking [9], and the study of the effectiveness of interventions aimed at reducing early childhood obesity [10].

SimNCD (*Simulation of NonCommunicable Diseases*) [11] is a formal ABM that aims to help researchers and health practitioners study and simulate the dynamics of NCDs. It models individuals that evolve within a social network, and behave while engaging in activities offered by their physical environment. SimNCD allows modeling, among other examples, social interactions, psychological risk factors, behavioral aspects, and environmental factors. However, some specific areas of the study of NCDs could fall beyond the reach of SimNCD, such as the genetic aspect or molecular biology.

In fact, agents in ABMs often rely on human-like reasoning mechanisms that can be based on mental attitudes, e.g. objectives, desires, beliefs, and preferences [12, 13, 14]. Such mechanisms allow them to understand their environment and make decisions that suit their local goals [13, 14].

This paper has three objectives:

- First, we are looking to propose a way to model a reasoning mechanism that describes the individual's attitude when choosing what to do (an activity to practice). For that, we rely on the available literature in epidemiology, as well as the decision-making.
- Secondly, we aim to provide a solution that allows public health practitioners to simulate and predict the influence of such choices on the individual's health.
- Thus, we extend SimNCD to include a mechanism that models such reasoning. This leads us to the third objective which is to test and illustrate the utility and extensibility of SimNCD.

To summarize, we focus on modeling a decision-making process based on the mental attitude of preferences.

*Corresponding author
Email address: rabia.aziza@gmail.com (Rabia Aziza)

The current paper is structured as follows. In Section 2, we briefly describe SimNCD. Then, we review the literature about modeling reasoning mechanisms in NCD ABMs. Section 3 proposes our solution: a preference based decision-making process for the study of NCDs. Then, we focus on the case study of childhood obesity, where we model the indirect effects of children's preferences on the development of their corpulence via their physical activity behaviors. The experimentation about this case study is described in Section 4. Finally, we conclude in Section 5.

2. Background

We begin by describing the formal model SimNCD [11] on which our method will be based. Then, we briefly review the literature about the elements that govern the choice of activities.

2.1. SimNCD: a formal model for NCDs

SimNCD is an ABM that models individuals living within a social network and engaging in activities available in their physical environment. The practice of these activities affects their inner state, i.e. the individual's characteristics including the health risk factors. It steers their health vulnerability to cure, acquire or maintain NCDs. SimNCD serves as a tool in public health policies for the study of NCDs where the individual's behavior greatly influences the predisposition to that disease. It is based on the approach IODA (*Interaction Oriented Design of Agent simulations*) [15]. In the following, we present its main components.

2.1.1. Agent families

An agent family means its category. It is an abstract specification of an agent [15]. The agents in SimNCD are either activities (e.g. take a walk, go to a party, work, and play) or individuals (children or adults).

The activities are part of the physical environment layer of the model. They are represented by the agent family A^{activ}, whereas the individuals constitute the social network layer and are represented by the agent family A^{indiv}.

2.1.2. Interaction

All behaviors in SimNCD are modeled as autonomic interactions (i.e. actions and communications) and organized in an interaction matrix [11, 15]. The overall functioning of an individual is as follows: among the perceived activities, each individual agent chooses one to practice, considered as the goal activity (this behavior is modeled as an interaction $I^{ChooseActiv}$). Then he/she moves towards its location (I^{Move}) and attempts to engage in it I^{Engage}). If the individual succeeds in doing so, he/she practices the goal activity. Finally, the individual quits the goal activity (I^{Quit}).

During the practice of the activity, the individual can exhibit different kinds of behaviors. SimNCD models them as instances of three abstract interactions that are to be instantiated when studying a specific NCD:

- Ψ^{indiv}_{indiv} models social communications, e.g. influence of friendship of the smoking behavior [16, 17].
- Ψ^{indiv}_{activ} describes an interaction with the physical environment, such as perceiving or modifying it, e.g. the influence of the environment on the walking behavior [9, 18, 19].
- $\Psi^{indiv}_{\emptyset}$ updates the individual's inner state, which is the health risk factors, e.g. influence of the physical activity on childhood obesity [11, 20].

All the interactions are presented in the interaction matrix (see Table 1), where each one is assigned to the corresponding source agent family that initiates the behavior, and the target agent family that is affected by it.

2.1.3. Health risk factors

SimNCD allows a thorough study of the evolution of the health based on dynamic personal and contextual factors that are directly or indirectly predisposing to NCDs. It describes an individual's inner state based on health risk factors, like $f^{energy\ intake}$ or $f^{smoking\ behavior}$. These factors can be biological, psychological, social, behavioral, factors from the physical environment, etc. [2, 5, 11, 21]. They influence each other via updates that can occur every time the individual practices an activity. An update is described as $\Psi^{set\ of\ source\ factors}_{set\ of\ target\ factors}$.

For instance, we can raise the cholesterol level, update the weight, change the mood, or renew friendship ties. In order to implement said updates, the designer adds an interaction that instantiates one of the three abstract behaviors Ψ^{indiv}_{indiv} ,Ψ^{indiv}_{activ} , and $\Psi^{indiv}_{\emptyset}$. For example, if we wish to model the influence of friendship (source factor) over the consumption of alcohol (target factor), we could declare two risk factors $f^{alcohol\ consumption}$ and $f^{friendship}$, then we add an interaction $\Psi^{f^{friendship}}_{f^{alcohol\ consumption}}$. This latter could inherit from the social abstract interaction Ψ^{indiv}_{indiv}.

2.2. Modeling agents in the study of NCDs

Agents in ABMs are often equipped with human reasoning mechanisms that allow them to understand and react to the changes occurring in their environment. Their modeling is based on information extracted from the social and physical environments, as well as mental attitudes, e.g. desires, beliefs, preferences, trust and reputation [12, 13, 14].

We focus on modeling agents in the context of NCDs. The literature proposes several models with different included risk factors, as well as diverse study objectives. Table 3 illustrates some examples from the literature. It describes the cognitive data and reasoning processes on which the proposed models are based.

Table 1: The behaviors in SimNCD are initiated by individuals (A^{indiv}). They are modeled as a set of interactions (I^{x}) and abstract updates ($\Psi^{set\ of\ source\ factors}_{set\ of\ target\ factors}$). They affect themselves ($\emptyset$), other individuals (A^{indiv}), or the physical environment (A^{activ}) [11]

Source agent family		Target agent family		
		$\emptyset$	A^{indiv}	A^{activ}
A^{indiv}	Interactions	$I^{ChooseActiv}$	-	I^{Engage}
		I^{Move}	-	I^{Quit}
	Abstract updates	$\Psi^{indiv}_{\emptyset}$	Ψ^{indiv}_{indiv}	Ψ^{indiv}_{activ}
A^{activ}		-	-	-

The cognitive data are basically thresholds and measures that describe a subjective point of view of an individual, such as preferences or attitudes [26, 36]. The proposed models often include the same concepts of mental attitudes. Yet these latter are mostly modeled differently depending on the context and the knowledge/data available to the study. For instance, both ABMs [9, 18, 19] model the attitude towards walking (the willingness to walk): in [19] it is calculated based on - among other data - the configuration of the streets in the neighborhood, whilst in [18] it is calculated based on a function of the individual's age and a random component, and in [9] the decision utility function takes into account the person's socioeconomic status and the time needed to arrive at the destination.

As for the reasoning processes, they depict the decision-making mechanism. They can be as simple as probabilistic and rule-based decisions [22, 23], or based on a more complicated reasoning, such as utility functions [9, 24, 25]. They rely on other information, like the taste preference [26] and the distance to school [27].

In our context, we aim to extend SimNCD with a reasoning mechanism in order to allow the simulated individuals to choose the activities they perform. As shown in Table 3, the literature proposes several models in which the individuals make a decision about their destination and move towards it [18, 19, 23, 24, 26, 27, 28]. The reasoning process in these models relies on data that are strongly dependent on the context and hypothesis of each study. Nevertheless, SimNCD is not specific to a particular disease or hypothesis. Therefore, we refer to the literature in order to find the elements of data that are necessary for the decision-making independently of the studied NCD.

The literature exposes the elements that arbitrate the choice of activities. These elements are mostly measured via questionnaires [29, 30, 31] that include a number of items. Each item has a set of possible scores.

For instance, the Preferences for Activities for Children questionnaire (PAC [29], see Table 2) is usually used for 55 activities, represented by cards that each child fills, e.g. the child specifies with whom he/she practices the activity. Then, statistics can be derived on, for example, the preference for a type of activities [32].

In the next section, we propose a solution for a reasoning process that uses these data in order to decide on the activity to practice.

Table 2: An extract from the questionnaire Preferences for Activities for Children (PAC) [29]

Items	Scores
Domain	Formal (organized, e.g. perform sports) or informal (e.g. gardening)
Type	Recreational, physically active, social, skill-based or self-improvement
With whom?	Alone, close family, other relatives, friends, others
Where?	Home, relatives home, neighborhood, school, in community, beyond community

3. Model design

We propose a reasoning mechanism as an extension to SimNCD that helps an individual select the activity that seems the most advantageous from his/her point of view. We express this point of view using preferences. As future work, other mental attitudes could be considered.

We model this mechanism in three phases. First, in the initialization phase, the person's preferences and the characteristics of the activities are described. Next, the person compares the characteristics of the candidate activities and his/her preferences. In this phase, the individual assigns evaluations to the candidate activities, hence the name: evaluation phase. Finally, the person selects the best activity suited to his/her liking in the selection phase.

3.1. Initialization phase

This phase is executed only once at the beginning of the simulation. It formalizes how (i) the individuals express their preferences and (ii) the activities describe their characteristics. Both steps are based on the same set of criteria.

3.1.1. Decision criteria

We extract the decision-making criteria from the questionnaires that are proposed by the literature. Let this set be $C = \{C_j\}$, where $j \in [1, n]$ and n is the number of criteria. The choice of the questionnaire can be done by the public health expert who's conducting the study. In this paper, we will base our examples on Table 1, in which case the obtained criteria would be: $C = \{C_1 = domain,\ C_2 = type,\ C_3 = social\ context,\ C_4 = physical\ context\}$.

Table 3: Examples of agent-based studies in the context of NCDs where the decision-making is based on mental attitudes

Goal of the study	Cognitive data	Reasoning process
Examining the effect of transport infrastructure on walking [9].	-	The choice of the mode of transportation (e.g. car, bus, walking) is based on a utility function that takes into account monetary cost and time.
The effects of peer influence and friendships on smoking prevalence [16, 17]	-	The children smoke according to a stochastic function based on individual and peer factors, e.g. friends and popular peers' smoking.
Environmental effects on the walking behaviors of individuals [18].	*Attitude towards walking:* a value that captures the individual's desire to walk. It is based on a function of the individual's age and a random component.	Individuals travel to their workplace, to grocery stores, and social places. The decision to walk depends on the walking distance threshold and the person's attitude towards walking.
Examining the interaction between walking preferences and the heterogeneity of the geographic physical environment [19].	*Walkability:* it reflects the person's willingness to walk to a destination (e.g. restaurant or library). It depends on the configuration of the streets, the accessibility of the destination, the pedestrian safety, the street attractiveness, etc.	The decision about where to walk in the neighborhood is made by choosing the destination with the maximum walkability.
The social influence on the corpulence variations of individuals [22].	*Body image ideal:* the ideal corpulence level (the mean Body Mass Index, BMI, of peers). *Satisfaction interval:* an interval that identifies the values of BMI that satisfy the person.	Rule-based decision mechanism: the agent increases or decreases its BMI in order to approach the ideal body image.
Examining some policies to improve urban food access for low-income populations [23].	-	Household agents make decisions to purchase food from food vendors at different frequencies. They either shop from supermarkets or food stores based on a probabilistic function.
Exploring patterns of leisure physical activity based on psychological traits and social environments [25].	*Intention:* the effort the individual would employ to engage in leisure-time physical activity.	Participation in leisure-time physical activities follow a utility function of the persons intention, influenced both by the social environment and the persons behavior.
The effects of different policies on unhealthy eating behaviors [26].	*Price sensitivity:* preference for cheaper food. *Taste preference:* preference for sweet and salty foods. *Health beliefs:* preference for eating healthily.	Individuals chose to consume 'fruits and vegetables' or 'fast food' based on their taste preferences, health beliefs, price sensitivity, food accessibility, and biological factors.
The impact of a program (where children walk to school in groups guided by adults) on children's active travel to school [27, 28].	*Attitude towards active traveling to school:* a value that reflects how much the child favors active traveling to school. It is influenced by the other children's attitudes.	The children choose the program if the safety of the route is above the household's concern, and the child's attitude is above a calculated threshold. Otherwise, they decide whether to walk or be driven to school.
Modeling the social network dynamics and their effect on the weight distribution in a given population [33].	*Attractiveness of alter's BMI:* a coefficient reflecting how attractive another person is based on the BMI. Its value is negative if the other person is overweight or obese.	The BMI is based on stochastic dynamics that take into account the BMI attraction and similarity between peers. BMI similarity reinforces friendships.
The disparities in the diet behavior corpulence within a population with racial differences [34].	*Healthy diet threshold:* a value that depicts the desirable level of healthy diet.	Rule-based decision mechanism: if an agent's healthy diet threshold is higher than the average healthy diet of its friends, it decreased its own healthy diet. Otherwise, it increased it.

We consider the scores of the criteria to be sub-criteria. Hence, each criterion C_j is a set of sub-criteria: $C_j = \{x_{ju}\}$, where x_{ju} is a linguistic term and $u \in [1, |C_j|]$. For example, $C_1 = \{x_{11} = \mathit{formal},\ x_{12} = \mathit{informal}\}$ and $C_3 = \{x_{31} = \mathit{alone},\ x_{32} = \mathit{close\ family},\ x_{33} = \mathit{other\ relatives},\ x_{34} = \mathit{friends},\ x_{35} = \mathit{others}\}$.

We now describe how the activities and the individuals use these items to model their characteristics and preferences.

3.1.2. Activity characteristics

Each activity describes its own characteristics according to the set of criteria C. We notice that some criteria can have more than one value. In Table 2, for instance, an activity can be practiced in different places or with different people.

We formally describe the characteristics of an activity β_i as: $\kappa^{\beta_i} = \{\langle C_j, \kappa_j^{\beta_i}\rangle\}$, where $j \in [1, n]$. $\kappa_j^{\beta_i}$ is the description of β_i regarding the criterion $C_j \in C$. It is a set of linguistic terms: $\kappa_j^{\beta_i} = \{x_{ju}^{\beta_i}\}$, where $x_{ju}^{\beta_i} \in C_j$, $u \in [1, |C_j|]$, and by consequence, $\kappa_j^{\beta_i} \subset C_j$. The fact that a characteristic $\kappa_j^{\beta_i}$ is a set covers the cases where more than one value can be attributed to a criterion. For instance, β_1 = "*Perform martial arts*" can be described with C_3 = "*social context*" as: $\kappa_3^{\beta_1} = \{x_{31}^{\beta_1} = \mathit{alone},\ x_{34}^{\beta_1} = \mathit{friends},\ x_{35}^{\beta_1} = \mathit{others}\}$.

3.1.3. Individual preferences

Regarding preferences, we consider them as a psychological factor f^{Prefs} that assigns a likeness degree in a Likert scale to each sub-criterion. Let L_M be a Likert scale of M terms. For $M = 3$, $L_3 = \{\tau_1 = \mathit{not\ like},\ \tau_2 = \mathit{like},\ \tau_3 = \mathit{really\ like}\}$. Therefore, to each sub-criterion x_{ju}, the individual assigns a linguistic term $\tau_i \in L_M$. We propose to describe the preferences as follows: $f^{Prefs} = \{\langle C_j, x_{ju}, \tau_{ju}\rangle\}$, where $\tau_{ju} \in L_M$ expresses the individual's likeness towards x_{ju} of the criterion $C_j \in C$, $u \in [1, |C_j|]$ and $j \in [1, n]$. Hence, f^{Prefs} includes as many elements as sub-criteria: $|f^{Prefs}| = \sum_{j=1}^{n} |C_j|$. For example, $f^{Prefs} = \{\langle C_1,\ x_{11} = \mathit{formal},\ \tau_{11} = \mathit{really\ like}\rangle, \langle C_1,\ x_{12} = \mathit{informal},\ \tau_{12} = \mathit{like}\rangle,\ \langle C_2,\ x_{21} = \mathit{recreational},\ \tau_{21} = \mathit{not\ like}\rangle,\ \langle C_2,\ x_{22} = \mathit{physically\ active},\ \tau_{22} = \mathit{really\ like}\rangle,\ \langle C_2, x_{23} = \mathit{social},\ \tau_{23} = \mathit{not\ like}\rangle, ...\}$.

3.2. Evaluation phase

Unlike the initialization phase, the evaluation phase and the selection phase are executed when an individual agent decides on the activity to practice. In the evaluation phase, a person uses the elements that we set previously in order to evaluate the candidate activities. The output of this phase is composed of evaluation sets for each activity.

In fact, the candidates are the perceived activities β_i. For each β_i, the person examines the characteristics $\kappa_j^{\beta_i}$ one by one, and assigns the corresponding likeness from the preferences f^{Prefs}, as represented in Figure 1.

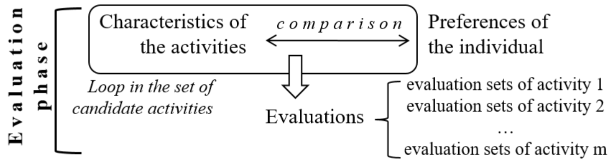

Figure 1: Evaluation phase

3.2.1. Formal description

We obtain a set of evaluations E^{β_i} that can be described as a relationship between the set of criteria C and the linguistic terms from L_M. These linguistic terms are not necessarily ordered because we intend to aggregate them later in order to obtain one value describing the performance of each activity (the aggregation is part of the selection phase). Therefore, we omit the sub-criteria from E^{β_i}. In other words, E^{β_i} describes the likeness levels to each criterion, e.g. $\langle C_3, \{\mathit{really\ like},\ \mathit{like},\ \mathit{like}\}\rangle$, instead of $\langle C_3, \{\{x_{31}^{\beta_1} = \mathit{alone},\ \mathit{really\ like}\}, \{x_{34}^{\beta_1} = \mathit{friends},\ \mathit{like}\}, \{x_{35}^{\beta_1}\} = \mathit{others},\ \mathit{like}\}\}\rangle$. We describe a set of evaluations as: $E^{\beta_i} = \{\langle C_j, e_j^{\beta_i}\rangle\}$, $j \in [1, n]$. $e_j^{\beta_i}$ is a set of linguistic terms from L_M that describe the preferences towards all the sub-criteria of the criterion C_j, retrieved from the characteristics of β_i. Hence, $e_j^{\beta_i} = \{\tau_{ju}\}$, where $\exists\langle C_j, x_{ju}, \tau_{ju}\rangle \in f^{Prefs}, \tau \in \tau_{ju} \in L_M$, the sub-criterion $x_{ju} = x_{ju}^{\beta_i} \in \kappa_j^{\beta_i}$ with $\langle C_j, \kappa_j^{\beta_i}\rangle \in \kappa^{\beta_i}$ (i.e. $x_{ju}^{\beta_i}$) is part of the characteristics κ^{β_i} of β_i). The terms of $e_j^{\beta_i}$ are not necessarily ordered, distinct, balanced, nor different.

3.2.2. Algorithm

In Algorithm 1, we present EvaluateActivity that constructs the set of evaluations of E^{β_i} of an activity β_i.

Algorithm 1 *EvaluateActivity*$(\kappa^{\beta_i}, f^{Prefs})$ calculates the evaluation of an activity

Require: κ^{β_i}: the set of characteristics of the activity β_i; $\kappa^{\beta_i} = \{\langle C_j, \kappa_j^{\beta_i}\rangle\}$, $j \in [1, n]$, $\kappa_j^{\beta_i} = \{x_{ju}^{\beta_i}\}$
f^{Prefs}: the set of preferences of the individual; $f^{Prefs} = \{\langle C_j, x_{ju}, \tau_{ju}\rangle\}$, $\tau_{ju} \in L_3$, and the sub-criterion $x_{ju} \in C_j$, $u \in [1, |C_j|]$ and $j \in [1, n]$
Ensure: E^{β_i}

```
initialize E^{β_i} to an empty list
for criterion C_j ∈ C do
    initialize e_j^{β_i} to an empty list
    for sub-criterion x_{ju}^{β_i} in κ_j^{β_i} do
        add {τ_{ju} | ∃⟨C_j, x_{ju}, τ_{ju}⟩ ∈ f^{Prefs}, and x_{ju} = x_{ju}^{β_i}}
        to e_j^{β_i}
    end for
    add {⟨C_j, e_j^{β_i}⟩} to E^{β_i}
end for
```

3.3. Selection phase

Once the evaluations are prepared, the individual agent selects the activity to practice. First, it aggregates the sets of evaluations for each activity, and then compares them in order to choose the preferred one. Since the evaluations are based on criteria with discrete evaluations (linguistic) and a finite number of solutions, we are facing a multi-attribute decision-making (MADM) problem [35, 36, 37].

3.3.1. Multi-attribute decision-making methods

The MADM allow the selection and classification of alternatives. They can be classified in four categories: elementary methods (e.g. Maximin), outranking methods (e.g. ELECTRE and PROMETHEE), utility methods (e.g. SMART and AHP) and others (e.g. SAW and TOPSIS) [35, 36, 37]. The choice of the method to adopt depends greatly on the available information regarding the criteria. Hence, we do not limit such choice in our model. An example will be illustrated in the case study.

3.3.2. Linguistic representation and aggregation

We look into how to represent and aggregate the information in the evaluations. In our decision-making problem, the evaluations are sets of linguistic terms: $e_j^{\beta_i} = \{\tau_{ju}\}$, $\tau_{ju} \in L_M$.

The MADM methods are usually applied to evaluations and not sets of evaluations. Therefore, we propose to aggregate each set of linguistic terms $e_j^{\beta_i}$ into one value $\tilde{e}_j^{\beta_i}$.

The multi-valued logic [38] brings a solution to this matter by providing a representation of vague, uncertain, or imprecise knowledge using the human language. It associates a symbolic representation with linguistic terms and allows to express the intermediary degrees of truth between the true and the false. For a given concept, the degrees of truth can be represented as a set: $L_k = \{\tau_1, \tau_2, ..., \tau_k\}$, $k \geq 2$ and $\forall i \geq 2, \tau_i \leq \tau_{i+1}$. In our context, we use the multi-valued logic to represent the evaluations that are expressed with linguistic terms in L_M.

We examine the linguistic aggregation operators (LAOs) proposed in the literature. They can be classified in four categories [39]: the LAOs based on a linear order [40, 41], the LAOs based on the extension principle [42], the LAOs based on symbols [43], and the LAOs based on continuous linguistic domain [39, 44]. The LAOs in the first three categories allow approximating the result of an aggregation. However, the fourth category produces an aggregation result that is more precise on a continuous scale. Thus, we choose the fourth category that includes the linguistic 2-tuple representation [44] and the method of virtual terms [39]. Both these methods extend the original discrete linguistic domain to a continuous linguistic set. The main difference between them is that the virtual terms method can return a linguistic term that doesn't belong to the original set. We opt for the linguistic 2-tuple representation [44]. In this numeric-symbolic model, a data is a linguistic 2-tuple, noted l^{2t}, composed of a couple $l^{2t} = \{s, \gamma\}$, where s is a term from the original discrete linguistic set, and γ is a numeric value expressing a translation degree from the term s. Thus, γ indicates how far l^{2t} is from s. If l^{2t} coincides with s, then $\gamma = 0$, otherwise $\gamma \in [-0.5, 0.5)$. This method proposes some LAOs, such as the weighted average and the induced weighted average [44].

3.3.3. Formal description

The input of the selection phase is the sets of evaluations $e_j^{\beta_i}$ per activity β_i and per criterion C_j. We present them in a matrix (a line per activity and a column per criterion):

$$\begin{array}{c} E^{\beta_1} \\ \cdots \\ E^{\beta_m} \end{array} \begin{bmatrix} e_1^{\beta_1} & \cdots & e_n^{\beta_1} \\ \cdots & \ddots & \cdots \\ e_1^{\beta_m} & \cdots & e_n^{\beta_m} \end{bmatrix}, e^{\beta_i} = \{\tau_{ju}\} \ and \ \tau_{ju} \in L_M$$

In this phase, we proceed as follows:

- We aggregate each $e_j^{\beta_i}$ into one 2-tuple linguistic term (e.g. using the 2-tuple arithmetic average [44]). We obtain the 2-tuple matrix:

$$\begin{array}{c} \tilde{E}^{\beta_1} \\ \cdots \\ \tilde{E}^{\beta_m} \end{array} \begin{bmatrix} \tilde{e}_1^{\beta_1} & \cdots & \tilde{e}_n^{\beta_1} \\ \cdots & \ddots & \cdots \\ \tilde{e}_1^{\beta_m} & \cdots & \tilde{e}_n^{\beta_m} \end{bmatrix}, \tilde{e}^{\beta_i} = (\tau_j^{\beta_i}, \gamma_j^{\beta_i})$$

- We use a MADM method, adapted and applied for the 2-tuple representation, in order to calculate the performance of each activity β_i.
- We select the activity with the best performance.

3.4. Case study: childhood obesity

In [11, 45], the authors proposed an ABM to simulate the children's physical activity and its relationship with obesity, called $SimNCD^{ChO}$ (SimNCD for Childhood Obesity). We briefly present this ABM, and then we extend it with our proposed reasoning process.

3.4.1. Context of the case study

$SimNCD^{ChO}$ [11, 45] models children who are engaged in activities that affect their health regarding acquiring or maintaining obesity. The included risk factors are:

- *Biological factors:* Age and gender.
- *Physical environment:* The opportunity to practice physical activity. This factor reflects the amount of Moderate to Vigorous Physical Activity (MVPA) offered by each activity. For instance, the opportunity of "playing at a park" is bigger than that of "playing video games". This factor is described as a percentage, and the sum of the opportunities of the activities practiced by a child in a physical environment that is favorable for a good health is 100%. The more such sum increases above 100%, the more the physical environment of the child is highly favorable, and the less it is, the more the physical environment is unfavorable.

- *Mental attitude:* The attitude towards an activity is a value in [0, 2]. This factor is inspired by the literature, such as the attitude towards active traveling to school [28] and the attitude towards drinking [46]. It reflects how far the child is motivated to take advantage of the opportunity that is offered by an activity. The higher the value of this coefficient, the more the child is considered to be active. This factor can be interpreted as unmotivated, motivated, or highly motivated.

- *Behavioral factor:* The physical activity, measured in daily minutes of MVPA. It can be interpreted as inactive, active or highly active. It follows the normal course of the children's physical activity via a function called $basicMVPA(age, gender)$. This function provides the amount of MVPA minutes each child would be engaged on account for the normal course of MVPA (more details can be found in [1, 11]). The physical activity also depends on the encountered opportunities (opp^{β_i}) and the child's attitude towards the activity β_i ($attitude^{\beta_i}$). By practicing β_i, the child gathers $MVPA^{\beta_i}$, calculated as follows: $MVPA^{\beta_i} = opp^{\beta_i} * attitude^{\beta_i} * basicMVPA(age, gender)$. The amount of MVPA gathered during a day is the sum of $MVPA^{\beta_i}$ of all the activities practiced during that day.

- *Physiological factor:* The corpulence, measured in Body Mass Index (BMI) and characterized as normal, overweight or obese. It follows the normal trends of development of the children's BMI as described in the children's growth references [47]. The corpulence factor is updated depending on the average amount of daily MVPA practiced over the year. The effect of the daily MVPA on the child's BMI was aggregated from results offered by the literature. This function is presented in details in [11].

This case study was validated against empirical data extracted from interventions [11]. A public health intervention is a set of actions involving a group of people. It aims to make changes to prevent or treat a disease [1].

3.4.2. Modeling the choice of the goal activity

We extend $SimNCD^{ChO}$ in order to include the proposed reasoning process. This latter interferes on two levels in our ABM. On the first level, it steers the child's behavior by allowing him/her to choose an activity. We use the questionnaire PAC for the decision criteria (Table 2). Besides that, in the selection phase, we use the MADM method TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), applied for the linguistic 2-tuple [37, 48, 49]. TOPSIS chooses the alternatives that are simultaneously the most advantageous and least costly. This is achieved by calculating a Relative Proximity coefficient $\in [0, 1]$, for each alternative.

This measure represents a subjective aggregated evaluation of an activity from the child's point of view. We refer to it as the function $RelProx^{2t}$. The selected activity is the one with the highest Relative Proximity value. This phase is summarized in Algorithm 2.

3.4.3. Modeling the effects of the preferences on the health

On the second level, the preferences affect the way the child practices the activities via the risk factor "attitude towards an activity". In fact, we suppose that a child takes as much advantage of an activity as the preference for this activity. In other words, a child who prefers an activity has a positive attitude towards it. We already have a coefficient that reflects the performance of each activity, which is the Relative Proximity. We use it to calculate the child's attitude: $attitude^{\beta_i} = RelProx^{2t}(\tilde{E}^{\beta_i}) * 2$, where $\tilde{E}^{\beta_i}$ is the vector of aggregated 2-tuple evaluations of the activity β_i. Since $attitude^{\beta_i} \in [0, 2]$ and $RelProx^{2t} \in [0, 1]$, this latter is multiplied by 2.

Algorithm 2 $SelectActivity(E)$ selects an activity based on the linguistic 2-tuple evaluations and TOPSIS

Require: E: the set of evaluated activities, $E = \{E^{\beta_i}\}$, $E^{\beta_i} = \{\langle C_j, e_j^{\beta_i} \rangle\},\ j \in [1, n],\ e_j^{\beta_i} = \{\tau_{ju}\},\ \tau_{ju} \in L_3$
Ensure: $Max(Performances)$
  let $Performances$ be an empty list
  for E^{β_i} in E **do**
    let $\tilde{E}^{\beta_i}$ be an empty list of linguistic 2-tuple terms
    for $e_j^{\beta_i}$ in E^{β_i} **do**
      $\tilde{e}_j^{\beta_i} = ArithmeticAverage^2t(e_j^{\beta_i})$
      add $\tilde{e}_j^{\beta_i}$ to $\tilde{E}^{\beta_i}$
    end for
    add $\langle \beta_i, RelProx^{2t}(\tilde{E}^{\beta_i}) \rangle$ to $Performances$
  end for

3.4.4. Summary of the child's behavior

The overall behavior of a child agent can be summarized as a loop of the following steps:

- Choosing the activity to practice:
  - Evaluating the activities based on their characteristics and the preferences.
  - Deciding on the activity to practices.
- Moving towards the chosen activity and practicing it.
- Updating the child's inner state:
  - Updating the age risk factor.
  - Calculating the attitude towards the activity.
  - Updating the MVPA based on the age, the gender, the opportunity to MVPA, and the attitude.
  - Updating the BMI based on the age, the gender, the current BMI, and the MVPA.
- Quitting the activity.

4. Results and discussion

We implemented $SimNCD^{ChO}$ with the framework JEDI [15] with an option to activate the reasoning process. We use this simulator to validate our ABM against empirical data. Then, we run it in different scenarios in order to predict insights about real children's corpulence variations.

4.1. Simulation for validation

Finding detailed data to help evaluate detailed prediction models such as SimNCD can be quite challenging [11]. Among other reasons, that is due to the fact that the field studies proposed by the epidemiological literature rarely include the same contexts, hypotheses, and factors.

To evaluate our model, we replicated the findings of field studies [50, 51, 52, 53] and compared the simulated results with the actual ones. The results obtained with the interventions [51, 50, 53] resemble those presented in [11]. In this paper, we detail the results obtained for the intervention of Li et al. [52].

We note that, in the validation, we do not focus on detailing the effect of preferences on the outcome of the simulations. We rather examine the overall results of our model to compare them with those reported from empirical studies. A discussion about the children's weight statuses specified by their preferences will be detailed in section 4.2.

The physical activity intervention [52] includes a population of 4700 children, assigned randomly to the control group (that did not follow a physical activity program) or the intervention group. This latter experienced an additional daily 20 min of MVPA at school. The study observes and compares the development of children's corpulence in both groups.

In our simulation, we included the following risk factors: age, gender, opportunity to MVPA (measured in percentage, with the sum of daily opportunities in a favorable physical environment is 100%), attitude towards the activities, and adiposity (measured in BMI, kg/m^2).

We started by reproducing the data of the controlled group over one simulated year. As described in [52], the sample size of the control group was 2115 children (1050 girls) of 9 years old, with a baseline BMI of $17.74 \pm 3.61 kg/m^2$ (mean $\pm$ standard deviation). Using these data, we initialized the number of children, their age, gender, and BMI. We set the preferences (by consequence, the attitude towards the practiced activities) to random. Since we didn't find information that qualify the physical environment in the paper, we supposed that the physical environment is favorable and we set the opportunity to MVPA to 100%.

Next, we configured the simulation of the intervention group as described in [52]: 2072 children (957 girls) of 9 years old, with a BMI of $17.79 \pm 3.61 kg/m^2$ at baseline. The preferences were set to random. As for the opportunity to MVPA, it was set to 100% plus the opportunity given by the daily 20 min/day of MVPA. To transform the minutes of opportunity to a percentage, we divided them by the normal course of children's daily MVPA (i.e. corresponding to a normal health), which is 60 min and 72 min of MVPA for, respectively, 9 years old girls and boys [1]. Thus, the opportunity to MVPA was (100%+20/60) for girls and (100%+20/72) for boys.

Figure 2 illustrates the results of the average BMI of both groups in the original and the simulated study. The obtained simulated effect of the intervention is $0.07 kg/m^2$. It is calculated by subtracting the BMI of the intervention group from the BMI of the controlled group. The results show that this value is close to the effect stated by the real intervention, $0.11 kg/m^2$ [52]. This suggests that our model is capable of delivering realistic indications about changes in the BMI of children. Such validation should be extended to cover all the studied age range, from 9 to 10 years old.

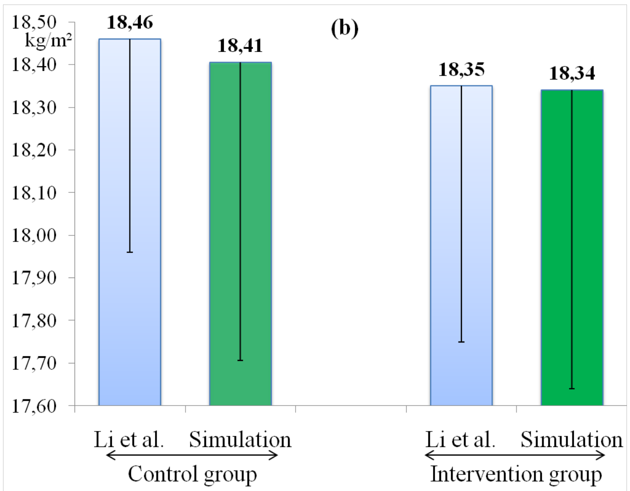

Figure 2: Comparison between the average BMI results of [52] and our simulations on a one-year scale.

4.2. Simulation for prediction

The presented reasoning mechanism allows simulating children with different preferences about the activities they practice in their daily lives. Such simulation would help researchers and health practitioners obtain insights about the development of the corpulence of real children with different preferences and physical activity behaviors.

4.2.1. Experimental design

The literature [54] suggests that the preferences of children are different from the preferences of adolescents. In this paper, we did not take into account the evolvement of the preferences with time. Therefore, we chose to simulate the development of the children during primary school (initialized at 6 years-old and simulated until 10 years-old). Hence, the results were gathered after 4 years when the children reached 10. The simulated characteristics are:

- Population: 1000 boys and 1000 girls.
- Different opportunities to MVPA offered by three activities:
  - Stay at home: a sedentary activity (such as playing video games).
  - Play at the park: a moderate activity.
  - Perform sports: a vigorous activity.
- The preferences of children were set randomly in $L_3 = \{not\ like,\ like,\ really\ like\}$.

We simulated three scenarios for both genders. The first scenario depicted children with normal BMI with a high risk to become overweight. The second scenario involved overweight children, and the third one was about obese children.

4.2.2. Results and discussion

The extended SimNCD allows making predictions (based on a mental attitude risk factor) than the original SimNCD model. We examined the changes in BMI in the different simulated scenarios (Figure 3) while taking into account the activities that the children perceived (i.e. the activities that were available to them) and the ones they preferred. The results were specified by the gender, the initial weight status (normal, overweight or obese), the perceived and the preferred activities.

At the end of the simulation, we noticed that the children who stayed at home (cases 'a') had noticeably higher BMIs than those who were engaged in a structured activity (like sports). This not only supports the claim that physical activity is a key factor in the dynamics of obesity [1, 2] but also proposes a more precise quantification of such relationship. For instance, overweight girls and boys who practiced sports had, respectively, up to 26% and 10% less BMI than those who remained at home.

We also noted that boys were more advantageous than girls in most simulations in terms of obesity risk. This suggests that overweight and obesity may be more difficult to overcome in girls than in boys, or that the relationship between PA and adiposity is stronger in boys, as suggested by the literature [47, 55].

In order to better understand the results, we computed children's BMI distribution in terms of risk at the end of the simulation, presented in Figure 4. As mentioned earlier, boys were more advantageous than girls, especially in the case of children initialized as obese, and even more for those who were overweight at baseline. However, that was not the case of the ones who had normal weight. In fact, 27% of the normal boys who practiced sedentary activities and 5% of those who practiced moderate activities (but did not perform vigorous activities) ended up as overweight. Nevertheless, all girls with normal weight remained as such, no matter the activity they preferred or engaged in. This might suggest that the hypothesis about girls being more disadvantageous than boys only applies to overweight and obese girls (we call this 'hypothesis 1').

Among the children who were initialized as overweight, girls had a much higher risk of becoming obese, especially those who were sedentary (93% became obese), compared to boys (only 6% became obese). Besides that, children who engaged in vigorous activities (sports) had a consistent chance at becoming normal: 52% chance for girls and 37% for boys. The overweight girls always had a risk to become obese, but the risk was lower (5%) when they were vigorously active.

On the other hand, some of the obtained results were conflicting. For instance, in the case 'c' of overweight girls (Figure 4), 40% of these girls had normal weight, 46% remained overweight, and 14% became obese. In our opinion, this can be explained by the fact that a given child takes advantage of practicing an activity as much as he/she likes it, i.e. via the attitude towards the activity that depends on the preferences. In some cases, even though a child performs sports, his/her corpulence might deteriorate. Thus, we can suppose that a physical activity, even a vigorous one, is not sufficient if not coupled with a positive attitude towards it ('hypothesis 2'). And since such controversy was only observed in overweight girls, we can assume that this age is quite critical for the development of their corpulence, more so than other girls/boys ('hypothesis 3').

As for children initialized as obese, the only cases where their corpulence improved were when they practiced moderate and/or vigorous activities (cases 'c' and 'd'). Based on these results, the best chances of obese children at becoming overweight were 12% for girls and 35% for boys. These results also suggest that performing vigorous physical activities is not enough to bring 6-year-old children from obesity to normal adiposity. This could call for additional efforts to be made on other risk factors, or it might require longer than 4 years of intervention in order to achieve a safe normal weight status ('hypothesis 4').

The hypotheses 1 to 4 call for further examination. Epidemiological field studies could be undertaken in order to verify them.

5. Conclusion

This paper proposes a reasoning mechanism, modeled as an extension of the formal ABM SimNCD [11]. This process uses an MADM method, applied to linguistic 2-tuple preferences.

Basically, this decision-making mechanism has three contributions. First, it allows the individual agents to reason and choose the best activity to practice. Secondly, it allows modeling the (in)direct effects of mental attitudes (in this case, the preferences) on a population's health. Thirdly, this work illustrates the use of SimNCD and its extensibility to include different kinds of risk factors.

We applied our solution in the study of childhood obesity and we extended the model $SimNCD^{ChO}$ [11]. We

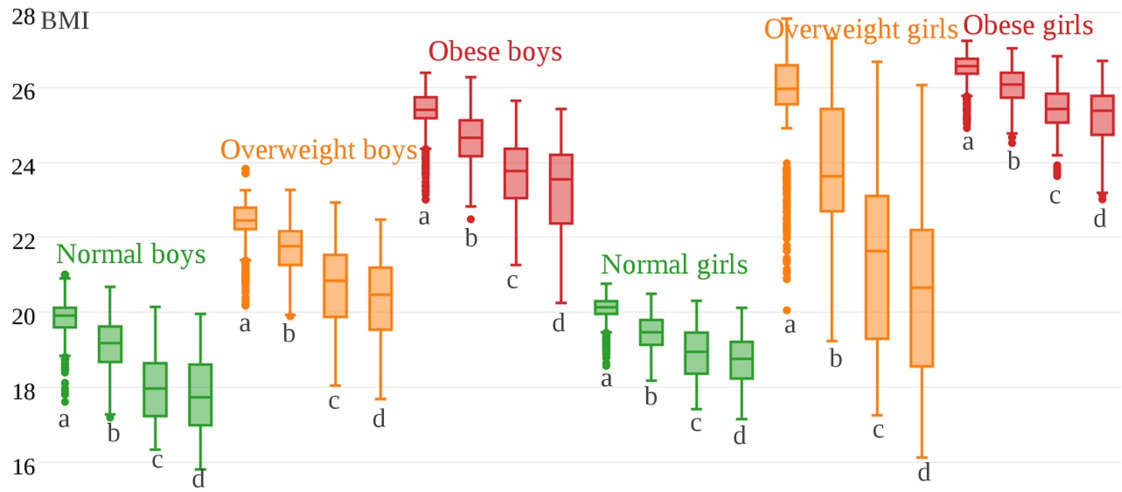

Figure 3: BMI results. The boys/girls were initialized as normal, overweight, and obese, with the preferences: a=stay at home; b=can stay at home or play at the park, and prefer playing at the park; c=can stay at home or perform sports, and prefer performing sports; d=can stay at home, play at the park, or perform sports, and prefer performing sports.

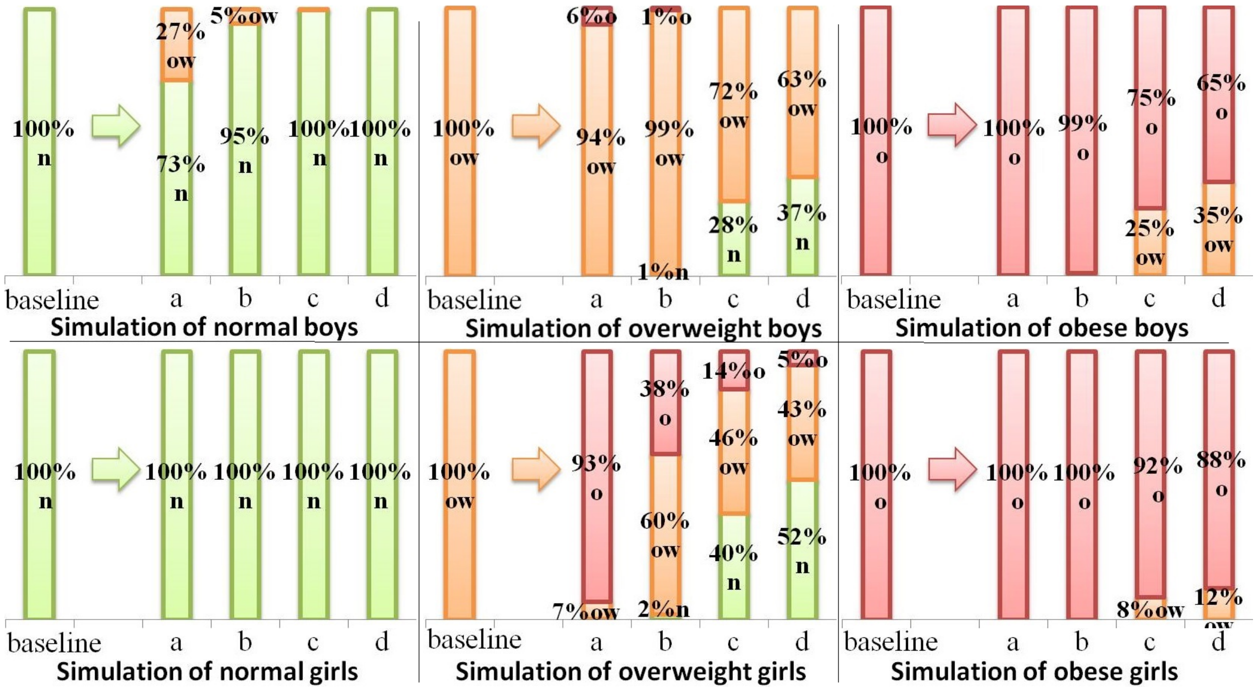

Figure 4: Distribution of the corpulence prevalence based on the BMI growth references [47]. In each scenario, all children have the same corpulence status at baseline (prevalence is 100%). Boys/girls were initialized as normal, overweight, and obese, with the preferences: a=stay at home; b=can stay at home or play at the park, and prefer playing at the park; c=can stay at home or perform sports, and prefer performing sports; d=can stay at home, play at the park, or perform sports, and prefer performing sports.

validated our system against empirical data. Then we used it to predict the indirect effects of children's preferences on the changes in their corpulence as mediated by physical activity behaviors. This system could allow the public health researchers and practitioners to simulate and examine the effect of the interplay between available activities in a physical environment and children's personal preferences on their health, as exemplified by the weight status in the present study. Furthermore, the simulations that we carried out allowed us to formulate some hypotheses that could bring more understanding of the complex dynamics of obesity.

As future work, the proposed cognitive mechanism should be tested in other domains. It could also be extended to take into account temporal changes in the preferences, or to include other mental attitudes in the reasoning process, such as beliefs and emotions.

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