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► **To cite this version:**

Rabia Aziza, Amel Borgi, Hayfa Zgaya, Benjamin Guinhouya. Physical Activity and Childhood Obesity: A Multi-Agent Simulation. DCAI 2014 - Distributed Computing and Artificial Intelligence, 11th International Conference, 2014, Switzerland Switzerland. hal-01718872

HAL Id: hal-01718872

<https://hal.science/hal-01718872v1>

Submitted on 1 Mar 2018

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Physical Activity and Childhood Obesity: A Multi-Agent Simulation

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Abstract. Engaging in a regular physical activity appears to be an important factor in the prevention of childhood obesity, which became one of the major public health challenges worldwide. The literature suggests that the relationship between physical activity and obesity is complex with many intervening factors that come from different aspects of the child's life. Yet, so far, the proposed models do not include all of the identified factors. The main objective of this study is to simulate the child's behavior within his/her social and physical environments in order to understand precisely the relationship between the PA and childhood obesity. This paper proposes a simulation model using the multi-agent paradigm.

Keywords: Complex Systems, Simulation, Multi-Agent Systems, Epidemiology, Childhood Obesity, Physical Activity

1 Introduction

Multi-Agent Systems (MAS) are widely used in simulating Complex Systems (CS). They simulate a CS by creating a virtual laboratory that imitates the original one. This helps understand the complex behaviors and phenomena that occur in a CS, such as emergence, stigmergy, adaptability, etc. [1]. It also helps predict for a better decision-making by simulating virtual experiments where scenarios can be tested. Moreover, it obviates the temporal dimension by simulating long periods in matter of seconds, and helps avoid the costs and effects of these tests on the real system [2]. For example, in the epidemiological field, conducting field surveys can be very expensive, especially if interventions need to be tested. A public health intervention is a set of actions that involves a group of people (in our context of study, it would involve children and their families). It intends to make changes in order to prevent or treat a specific disease [3]. A MAS that models a virtual field (as faithfully as possible to the

real field) would facilitate understanding the CS's often non linear behavior, and eventually, simulate interventions, predict their results and propose the best strategies to decision makers. Our research lays in the context of childhood epidemiology. It aims to portray the complex relationships between physical activity (PA) and childhood obesity. We use MAS to simulate the daily life of schooled children. This model would take into account the complex interactions between obesity and PA (and related behaviors such as sedentary behavior) while including the large number of factors involved (social, environmental, mood, health, etc.) [4].

The paper is structured as follows. In Section 2, we explain our application context and explain the choice of MAS as paradigm for our simulation. The following section proposes a multi-level MAS architecture and discusses its different components in Section 3. Finally, we conclude with a glance on future work in Section 4.

2 PA and Childhood Obesity in the Literature

2.1 The Relationship between PA and Childhood Obesity

At the beginning of 21st century, awareness of the extent of obesity and its strong negative impact on individual's health and healthcare systems has increased. In fact, it became one of the major public health challenges worldwide, and the WHO even uses the term “Globesity” to describe it [5]. Engaging in a regular PA appears to be an important factor in the prevention of obesity and several other chronic non-communicable diseases [Fig.1]. In his book [6], Guinhouya states that: *“the implementation of quality effective interventions first requires a better understanding of the natural history of common forms of obesity in relation to physical inactivity...”*

In the context of children and adolescents, assessing the PA behavior is particularly difficult”. For those reasons, this study is an attempt to model the multifactorial link between PA and obesity for 2 to 18 years old children.

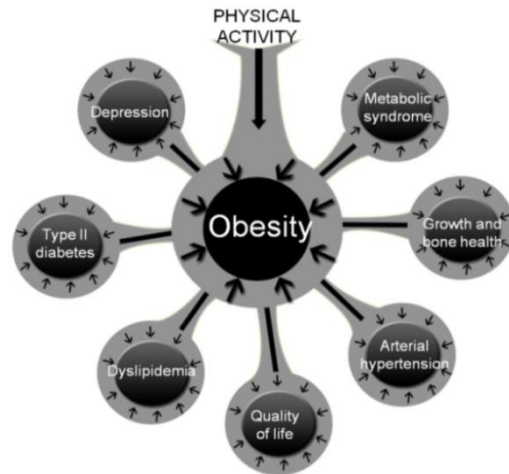


Fig. 1. Obesity as inducer of several diseases and the influence of PA on these diseases through its action on infantile obesity [6]

2.2 Overview of Studies on Modeling PA and Obesity

In the literature, most of the data that fall within the context of our research are epidemiological studies that focus on a subset of the predisposing factors to PA, obesity

and/or sedentary behavior (such as depression, self-esteem, neighborhood security, etc.) [7, 8]. The other studies propose mathematical models (mainly based on differential equations and stochastic processes) [9–11], and systemic models (e.g., rule based systems, MAS, etc.) [12, 13]. We are interested in studies that include and examine the relationships between obesity and PA in children. For instance, some authors [9, 11] propose mathematical models that displayed obesity as a social phenomenon, and – among other factors – include PA in their modeling strategy. Dangerfield et al. [10] also proposed a mathematical model for obesity. They have targeted 2-15 year old children, and included both PA and energy intake.

In fact, systems that focus only on either obesity [12] or PA [13] help us understand each one of them, but do not allow an understanding of the complex relationship between them. On the same subject, Guinhouya [6] argued that most interventions aiming to prevent infantile obesity by improving the PA behavior do not take into account all dimensions interfering with the matter, namely, the child’s social and physical environments, his/her psychological state, etc. In [14], the authors classified these factors as: demographic, psychosocial, physiological, biological and genetic, factors in the physical and social environments, economic and social status, and motor skills. Each one of these categories is a set factors. Therefore, we can consider factors and their relationships as a graph with complex interactions [10, 11, 14].

This study proposes a model that allows including all the mentioned factors and their relations from a complexity theory point of view. In fact, a CS’s behavior is guided by its details rather than general laws: all agents (in our MAS, agents represent persons) contribute to its functioning through micro movements [15]. Because of that, it is important to model the agents’ micro-movements and inner state details.

2.3 MAS for Modeling the Relationship between PA and Childhood Obesity

The complex relationship between PA and childhood obesity depends on the different factors discussed in the previous section. These factors come from different aspects of a person’s life: his/her social life, physical environment, feelings, physical health state, etc. Modeling this complex relationship needs to take into account the autonomy of persons, their links with their environments (physical and social), their behavior’s heterogeneity, and their cognitive mechanisms. As the MAS paradigm considers all these aspects and levels, we chose it to simulate children’s behavior within their environment. In fact, the MAS paradigm represents physical and social environments without limiting the agent’s autonomy (his independence of physical and social environments, unlike Cellular Automata [16] for example). Besides that, Bonabeau [17] stated that MAS paradigm is the only one facing the challenge of modeling social systems, because it can take into account, among other things, human behavior, complex reasoning and psychological factors. In addition, agents in a MAS evolve based on a complex set of rules that can differ from one agent to the other. This allows agents to have heterogeneous behaviors [18]. In order to simulate the agent’s micro movements, we focus on the schooled children’s environment, and we model their daily activity behaviors.

3 The Proposed Multi-Level MAS Architecture

Each individual evolves within a physical environment and communicates with his/her social network while updating his/her inner state. The proposed architecture [Fig. 2] is based on two levels: the environmental level and the intra-agent level.

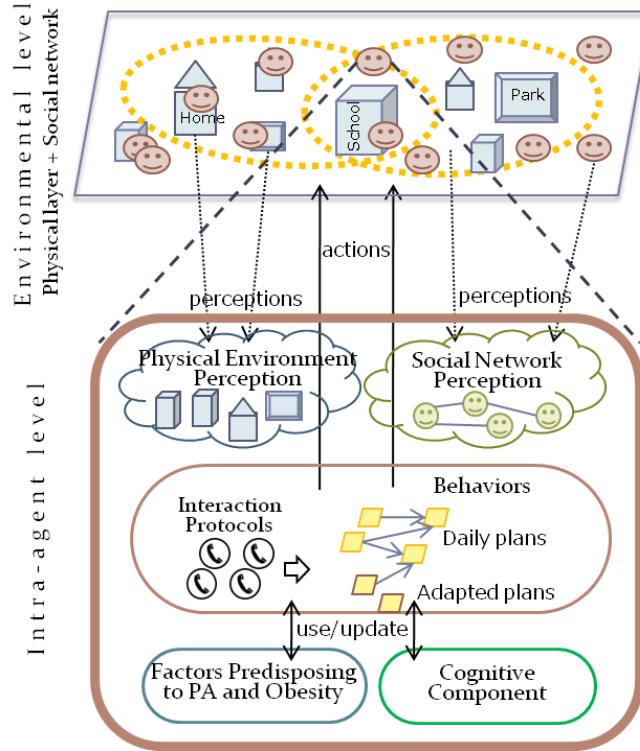


Fig. 2. The proposed multi-level MAS architecture

3.1 Environmental Level

Physical Environment. This layer is composed of neighborhoods. Each neighborhood contains a set of physical components (e.g., home, school, park, path, etc.) simulated by a set of classes. A physical component can offer simple activities (e.g., play, study, eat, sleep, etc) and traveling activities (e.g., take the bus, walk, drive by car, etc.). Each activity represents an atomic task an individual can do. It describes:

- a set of conditions for individuals, such as the conditions they need to satisfy in order to practice that activity (age, parental permission required, etc.),
- a list of individuals that are currently performing this activity,
- the effects that this activity applies on these individuals. For example: altering the individual's preferences, his/her mood and perception of the agents he/she contacted during the activity, and the current physical component. One of the challenges of this research is to accurately specify the effects of each activity.

Social Network. The social layer contains a set of individuals simulated by person agents (*PersonA*). These agents can be either children (*ChildA*), or adults (*AdultA*). *ChildA* and *AdultA* inherit from *PersonA* [Fig. 3]. The social network reflects relationships between persons and the roles they hold in these relationships. It can be described as a global variable. For instance, this variable would keep a graph of all social relationships in the MAS, and the role each person plays in a relationship. This would suggest that the higher level (system level detaining the variable) mandates rules/laws on the lower lever (*PersonA*). With such an approach, the agent's behavior is boxed and the possible actions he would make would be limited. According to CS modeling and MAS paradigm, relationships between agents should be managed and owned by individuals themselves. Therefore, we dispatch the social network across persons: relationships are represented within every *PersonA*'s perception of his social network. And the macro social network would result from the addition of all micro social perceptions.

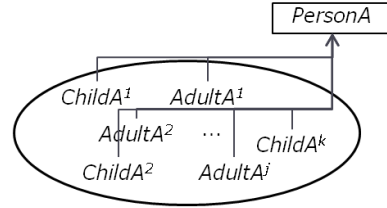


Fig. 3. Agents in the social network layer

3.2 Intra-Agent Level

This level focuses on describing the internal components of each individual. In fact, *PersonA* are cognitive agents. They must have the following elements that help them perceive, plan and act [19]:

Perception Components. In a MAS, an agent interacts with the world around him based on his own perspective. He is provided with mechanisms and abilities that allow him to perceive his physical and social environments. These perceptions are updated as he interacts, and depict knowledge that is embedded within the agent himself [19]. Thus, perception is by definition subjective. It can be updated, and can be correct, false, partially false or incomplete. For example, a person could think that a physical component offers a given activity while the latter is no longer available.

In our MAS, a person needs to perceive both social and physical environments:

- Perceived physical environment: In our model, an agent's perception of his physical environment is information (stored in his memory) about a subset of physical component objects; the ones that the agent knows about. And this knowledge is updated as he grows and interacts with his physical and social environments. For example, update via social interaction can happen when, throughout interactions, persons share some information about what they know (perceive) regarding the physical components and the possible activities they offer.
- Perceived social network: It allows an individual to have social relationships as well as a point of view about the persons he knows. The social perception is therefore a subset of *PersonA* with roles and subjective evaluations assigned to each one

of them. The roles allow the description of the relationship's nature (parent, son, friend, instructor, etc.). As for the subjective evaluations, they depict *PersonA*'s opinion about others (his feelings towards other agents, how close they are, etc.). Evaluations are expressed using social measures of the cognitive component.

Cognitive Component. This component allows agents to have human reasoning mechanisms. This part is being currently studied. A first analysis of our system's needs lead us to choose to model preferences and evaluation measures of both perceived physical environment (evaluation of the activities, e.g., what activities does an individual prefer) and perceived social network (evaluation of other individuals, e.g., social influence between two agents).

Factors Predisposing to PA, Sedentary Behavior and Childhood Obesity. The more factors and inter-factor relationships we cover, the more accurate and precise the simulation will be. In fact, it is the dynamic of the factors' network that will help us clarify the complex relationship between PA and childhood obesity. Some of these factors can be calculated based on other intra-agent components. For instance, we can use the agent's social perception and cognitive state to determine some of his psychosocial factors. The factors to be included first are the ones that are mostly encountered in the epidemiological literature. We will also try to inject factors that belong to different categories stated in [14]. An analysis of the field studies will allow us to specify how to measure and evaluate these factors, and what relationships (influence) they have on each other. In fact, the evaluation of a measured factor is expressed semantically. For example, most PA studies in children evaluate this behavior by using the set of ordered linguistic terms {Sedentary Activity, Light PA, Moderate PA, Vigorous PA}. Moreover, the different studies do not propose the same evaluation rules. Such imprecision on one hand, and the use of linguistic variables on the other, lead us to use Fuzzy Logic [20] to represent the considered factors. As for the relationships (such as the influence of the socioeconomic status on PA), they can be described via rules that are also retrieved from epidemiological field studies.

Behavior Component. The agent's behavior is guided by decision-making mechanisms that rely on information from other components. In our model, the life of an individual is simulated by a sequence of activities, allowing him/her to evolve and update his/her social relationships, internal state and perceptions. Therefore, an agent's behavior is modeled as a set of activities, and is organized as daily plans: each plan describes a schedule of activities to be performed during one day.

In order to promote the heterogeneity of agents, we provide them with a mechanism that allows them to follow different plans. In order to do so, different kinds of agents automatically have (more or less) different sets of possible plans, depending on the agent's roles (for *ChildA*: son/daughter, brother/sister, classmate, student, etc. and for *AdultA*: parent, teacher, instructor, etc.). Besides that, every agent is able to modify his plans according to his own will (he relies on his preferences, perceptions, history, etc.). This way, agents will autonomously adjust their plans and create new ones

that may be more suitable for them (mentioned as ‘Adapted plans’ in [Fig. 2]). This ability to adapt one’s plan is submitted to the activities’ conditions (described in [§3.1]).

The agent’s behavior is influenced by the other intra-agent layer components (perceptions, factors and cognitive mechanisms). At the same time, performing the different activities updates the agent’s cognitive component and the factors predisposing to PA and obesity. Besides that, the agent’s behavior changes the physical environment and the surrounding social relationships.

Interaction Protocols. This component describes the different possible interactions within the perceived social environment. In our MAS, we identify the following communication protocols (*PersonA – PersonA*):

- Data Sharing: These protocols allow agents to transfer information to each other. This knowledge can be simple objective data (for example, the parent sends to the child ‘today I went jogging for 1 hour’) or subjective information (like transferring one’s perception, e.g., the parent sends to the child ‘I am satisfied with your studies’). This kind of communication will guarantee updating the agents’ mutual perceptions. The agents involved are the ones considered to be close enough to perceive each other and share information – close from a social perspective (parent/child) or a spatial perspective (children playing at the same park).
- Other communications: Since we chose to simulate behaviors as a schedules of activities, agents will need to communicate about these activities on different occasions, such as asking permission to perform an activity (like permission to play outside), suggest an activity (offer to go to the park), negotiate an activity (negotiate the time allowed for TV), request to be accompanied to an activity (can be seen as a coordination protocol. Like asking to play a sport together), etc.

4 Discussion and Perspective

In this paper, we have proposed a general MAS architecture for modeling the environment within which evolve the dynamics of the complex relationship between obesity and movement behavior in children. Compared to existing studies, this one considers the model from a CS standpoint, and therefore focuses more on lower level details and relationships between elements. Besides that, the proposed model would allow including most of the factors that are identified in literature as predisposing to PA and obesity in children. The use of learning mechanisms (such as data mining and artificial learning) could help us identify factors and inter-factor relationships that are still unknown in literature. The proposed architecture could be used to study other non communicable diseases where the agent’s behavior greatly influences the factors predisposing to that disease, such as type II diabetes, depression, dyslipidemia, etc.

This work must be completed at different levels, particularly in modeling communication protocols, factors and cognitive mechanisms. Furthermore, the next step is the development of a simulator to test the model, and eventually test interventions.

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