

## Agent-Based Model for Studying Diabetes under the Influence of Relationships

Mateo Restrepo Sierra

Juan Sebastián Cárdenas-Rodríguez

Mathematical Engineering  
Universidad EAFIT  
Medellín, Colombia

Mathematical Engineering  
Universidad EAFIT  
Medellín, Colombia

David Plazas Escudero

Mathematical Engineering  
Universidad EAFIT  
Medellín, Colombia

### ABSTRACT

Diabetes is a disease which affects levels of blood insulin and recently has turned into a public health threat. This disease presents a huge risk for the individual, as it can reduce life expectancy. Furthermore, many models of diabetes just focus on biological or eating habits, without taking into account social or cultural factors. In this work, an agent-based model is proposed for the diabetic population taking into account interpersonal relationships and body mass index. The model is implemented in NetLogo and validated by results under extreme conditions. Then, it is simulated to test the influence that marriage has on the diabetic population. Finally, a sensitivity analysis is made.

**Keywords:** agent-based modeling simulation, diabetes, glucose levels, social interactions, compartment dynamics.

### 1 INTRODUCTION

Diabetes is defined as “Diabetes is a chronic, metabolic disease characterized by elevated levels of blood glucose (or blood sugar)” (World Health Organization 2019a). It can affect any kind of person, independent from his gender or age. Some studies suggest that the prevalence of diabetes will increase by 35% between 1995 and 2025. Additionally, the World Health Organization (WHO) and the World Bank consider diabetes as a public health threat (Altamirano 2001). Furthermore, (Atlas 2015) shows that diabetes can generate more complicated diseases, reducing life expectancy. On the other hand, regarding obesity:

*“Overweight and obesity are defined as abnormal or excessive fat accumulation that presents a risk to health. A crude population measure of obesity is the body mass index (BMI), a person’s weight (in kilograms) divided by the square of his or her height (in metres). A person with a BMI of 30 or more is generally considered obese. A person with a BMI equal to or more than 25 is considered overweight. Overweight and obesity are major risk factors for a number of chronic diseases, including diabetes, cardiovascular diseases and cancer. Once considered a problem only in high income countries, overweight and obesity*

*are now dramatically on the rise in low- and middle-income countries, particularly in urban settings.*"(World Health Organization 2019b)

The goal of this work is to extend the model proposed in (Bowes 2019), enhancing it with interpersonal relationships. The original model characterizes the dynamics of diabetes patients in the U.S. given their eating habits and the influence that they have on the glucose level. The population is classified into three types: healthy, risky and diabetic; individuals can change their state at any moment.

(Kahn and Flier 2000) affirms that there is an association between obesity and diabetes since obese individuals develop resistance to insulin. Motivated by the above statement, we propose an extension that consists of how social interactions affect eating habits and therefore diabetes. To achieve this, (Jeffery and Rick 2002) was studied for linking marriage and levels of BMI; moreover, in (Bays, Chapman, Grandy, and Group 2007) the association of BMI and diabetes is presented.

## **2 CONCEPTUAL MODEL**

### **2.1 Generalities**

#### **2.1.1 Model Objective**

The principal idea of this research is to explore the influence of relationships on diabetes, through eating habits.

#### **2.1.2 Entities and State Variables**

We consider individuals as agents, which have different state variables: diagnosis, BMI, glucose level and marital status. The diagnosis can be healthy, risky and diabetic. The BMI is measured in  $kg/m^2$ . The glucose in  $mg/dL$ . Finally, marital status is a boolean.

#### **2.1.3 Time Management**

As changes in glucose and BMI are not immediate, as they have gradual changes over time, it was decided to measure this state variables each 6 months.

## **2.2 Design Concepts**

### **2.2.1 Basic Principles**

As the model links different topics, each connection is supported by an article.

For the marriage dynamics, we refer to (Billari, Prskawetz, Diaz, and Fent 2007). This work developed an agent-based model (ABM) to characterize the marriage based on social interaction. They consider the complete life cycle of each individual, where the marriage is influenced by the social pressure of their relatives and their age.

As previously mentioned, the work from (Jeffery and Rick 2002) presents how marriage alters the BMI of the couple. This work found an association between change in participant BMI and change in marital status. Additionally, it affirms that the BMI cannot predict the likelihood of marriage or divorce, highlighting the importance of the work from (Billari, Prskawetz, Diaz, and Fent 2007).

In the same way, (Bays, Chapman, Grandy, and Group 2007) presents results regarding the probabilities of individuals having diabetes given a certain BMI.

Some simplifications were made: agents have a fixed age, between 21 and 33; the model does not include birth and death rates, the population is constant; however, marriage has a random predefined duration, which can be interpreted as death and therefore two new individuals arise; finally, we do not strictly consider heterosexual relationships, marriage is created only by physical distance and social pressure.

### **2.2.2 Emergence**

We consider four different outputs: the number of individuals with each type of diagnosis, and the married population. All outputs emerge as results of the interaction between the agents and the defined decision rules.

### **2.2.3 Adaptation**

The agents change their eating habits depending on the type of patch or their diagnosis. Each patch represents an eating habit, they are classified into two different kinds: pink patches symbolize healthy eating habits and black patches bad habits.

Moreover, eating habits can also be modified depending on marital status, and marriages depend on the number of married relatives. The relatives are chosen randomly at the beginning of the simulation.

### **2.2.4 Objectives**

The agents pursue marrying other people, regulated by the social pressure they feel by their relatives, which regulates their desire to pursue the objective. The social pressure is calculated by eq. (1).

$$sp = \frac{1}{1 + e^{-\beta(pom - \alpha)}} \quad (1)$$

Furthermore, they marry agents only in a certain age range. If  $x$  is the age of the individual, the range for the desired age of their partner is calculated in eq. (2).

$$\text{desired age} \in x \pm c \times a_i \times sp \quad (2)$$

Also, they search for a partner in a certain radius calculated in eq. (3).

$$d = a_i \times sp \times \frac{50^2}{N} \quad (3)$$

Lastly, healthy individuals pursue that other people have unhealthy habits. Similarly, diabetic and risky population desire that other agents eat healthy.

### **2.2.5 Learning**

We consider the model without learning since agents do not acquire information from previous states. The unique factor that can be considered as learning is that they change their eating habits based on their diagnosis, but it is not long-term knowledge.

### **2.2.6 Prediction**

The model does not consider prediction by agents.

### **2.2.7 Sensing**

From the environment, agents sense the patch, as previously mentioned, to change the eating habits. From themselves, they know their diagnosis to also modify the food habits. Explicitly, agents sense the patches; implicitly, they know their relatives that influence the marital status.

### **2.2.8 Interaction**

Agents interact only with their relatives and the person they married. Previously we specified that these interactions affect their marital status and eating habits respectively. The social pressure occurs only when an agent is not married.

### **2.2.9 Stochasticity**

The model considers randomness in several factors:

- Gender: the gender is assigned with equal probability to each agent once it is created.
- BMI: the initial BMI for each agent is assigned randomly depending on their diagnosis.
- Relatives: each individual has  $\lfloor N/10 \rfloor$  which are selected randomly.
- Diagnosis update: given a BMI, the patient is label as diabetic with a certain probability.
- Physical movement: agents move randomly in a 2-dimensional space.
- Initial glucose: random number between 80 and 100 for healthy, between 105 and 120 for risky and between 120 and 130 for diabetic.

### **2.2.10 Collectives**

Clearly, there are different kinds of collectives. First, the relatives of each individual and, second, the partner of each agent. These first two collectives influence the dynamics as described in previous sections. Lastly, the three diagnoses can be interpreted as collectives as well.

## **3 BACKGROUND**

In (Nejad, Martens, and Paranjape 2008), the authors propose an agent-based simulation (ABS) in order to assist patients to understand the effects of uncontrolled sugar and insulin levels. The paper transforms input variables such as food, exercise, medication, age, ethnicity, and gender into outputs such as blood glucose and blood pressure. This work confirms that there is a direct relation between these factors and that ABS is an adequate tool for modeling diabetes.

Furthermore, (Martínez, Hernando, Gómez, Villares, and Mellado 2012) proposes an ABS model that represents a fragment of a pancreas of a mouse. Two types of cells are modeled as agents in a three-dimensional space. The two described papers suggest that diabetes is suitable to be analyzed from different approaches, from a really wide perspective, such as general attributes of an individual, to really specific components of the insulin dynamics.

Moreover, (Montagna and Omicini 2017) introduces an ABS to study and monitor the state of the patient's health and provide suggestions for self-management.

Finally, (Dubovi and Lee 2019) presents a study of how an AB model can improve students learning, specifically, in the context of diabetes. The study concludes that the implemented model, in NetLogo, improves the learning quality, mostly due to real-time simulation and the graphical interface. This supports the implementation in NetLogo.

## **4 MODEL INPUTS**

### **4.1 Inputs**

The implementation uses as input the initial population for each diagnosis: it is modeled by a slider in NetLogo.

### **4.2 Parameters**

The implementation uses as input the initial population for each diagnosis: it is modeled by a slider in NetLogo. As for parameters:

- Number of relatives: it is modeled in the form  $\lfloor N/k \rfloor$ ,  $k \in \mathbb{N}$ .
- Gender probability.
- Initial glucose.
- $\alpha$  and  $\beta$  from social pressure (eq. (1)).

- $c$  and  $a_i$  from the radius (eq. (3)).
- Number of ticks before updating BMI.
- Probabilities relating BMI and diabetes (table 1), based on the work from (Bays, Chapman, Grandy, and Group 2007). In this table,  $D$  is the event of a person getting diabetic, and  $x_0 < \text{BMI} < x_1$  is the event of the BMI being in the specified interval.

$(x_0, x_1)$	$P(D x_0 < \text{BMI} < x_1)$	$P(x_0 < \text{BMI} < x_1 D)$
(15, 18.5)	0.005	0.032
(18.6, 24.9)	0.122	0.134
(25, 26.9)	0.103	0.044
(27, 27.9)	0.178	0.057
(30, 34.9)	0.261	0.111
(35, 39.9)	0.155	0.165
(40, 60)	0.176	0.461

Table 1: Probabilities.

- Changes of BMI according to marriage and gender (table 2) from (Jeffery and Rick 2002).

Marital status	Men	Women
Became unmarried	$-0.27 \pm 0.33$	$-0.63 \pm 0.27$
Became married	$0.70 \pm 0.24$	$0.96 \pm 0.30$

Table 2: BMI range of changes.

## 5 IMPLEMENTATION

The implementation was developed in NetLogo. We use sliders to initialize each type of population. Each turtle represents an individual which interacts with other turtles, modifying its marital status and its BMI. Consequently, the diagnosis changes.

Also, the agents interact with the environment, modeled as patches that change depending on the agent's diagnosis. Turtles randomly move in the 2-dimensional space.

The color on each patch represents how the next agent that touches this patch will eat. When this agent leaves the patch, it is updated according to its diagnosis corresponding with the following relations:

- Healthy and pink patch  $\rightarrow$  reduce glucose and patch turns black.
- Healthy and black patch  $\rightarrow$  increase glucose and patch remains black.
- Risky (or diabetic) and pink patch  $\rightarrow$  reduce glucose and patch remains pink.
- Risky (or diabetic) and black patch  $\rightarrow$  increase glucose and patch turns pink.

The original model considered was proposed by (Bowes 2019). It only changed the glucose level according to the patch, and then updated the state of each turtle in relation to the current glucose level. He considers that when an individual is diabetic, it can only change directly into healthy, without being risky.

We modified the original model adding the following attributes:

- Gender.
- BMI.
- Age.

- Marital status (marriage duration).

Moreover, the following decision rules were added:

- The marriage is arranged depending on the agents in the radius calculated with eq. (3) and encouraged by social pressure (eq. (1)).
- Diabetic individuals change into risky rather than directly to healthy.
- The BMI is updated according to the rules defined in table 2.
- The first column of table 1 is used to initialize the BMI of diabetic individuals. The second column of table 1 is used to update the population: it represents the probability of, given a BMI, the agent is diabetic.
- The rules for patch colors and glucose are already described above.
- Agents only marry other agents with an age range calculated with eq. (2).
- The model updates the BMI of married agents every 4 ticks, and of single agents every tick.

## 6 VALIDATION AND VERIFICATION

The model was validated through its response to certain simulation conditions. In this section, all simulations are executed for 1500 ticks.

The first simulation was performed using zero initial population and, as the model does not consider births, the number of agents should remain in zero. The results are presented in fig. 1. Note that the model behaves as expected.

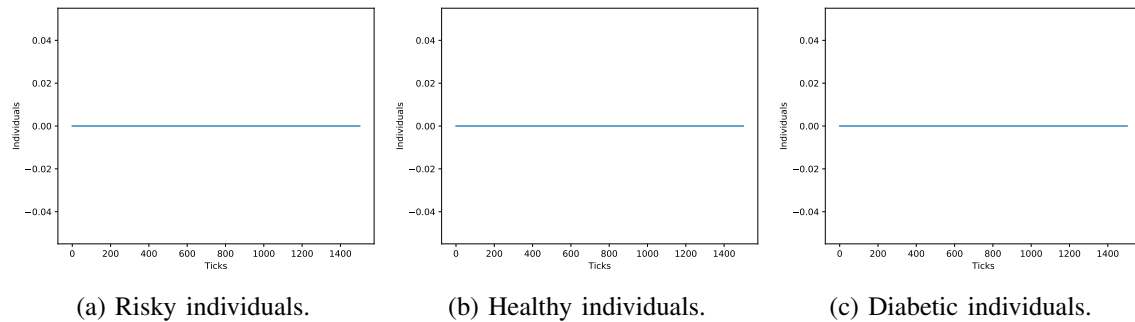


Figure 1: Results for zero population.

As our model considers that the BMI can only be modified by marital status, if we consider a radius of zero, agents could not marry anyone, since no agent can be found within the radius. Thus, the number of married individuals should remain in zero and the BMI should stabilize rapidly. This can be verified with the obtained results from fig. 2. The used populations were: healthy (71), risky (10) and diabetes (29).

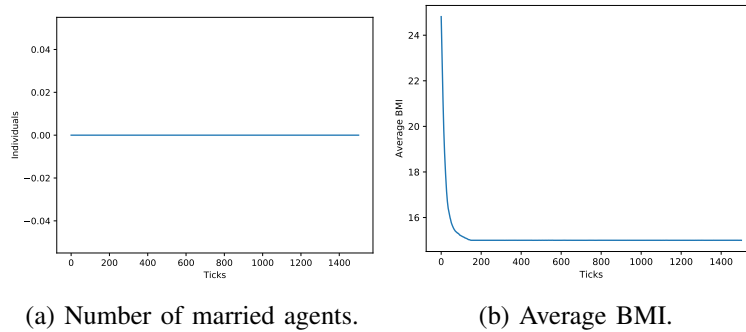


Figure 2: Results for zero radius.

Next, we considered a radius of  $10^6$ . The populations are the same as the previous experiment. fig. 3 partially supports what was hypothesized, that is, the number of married agents oscillates around the total population size. However, the BMI decreases for unknown reasons.

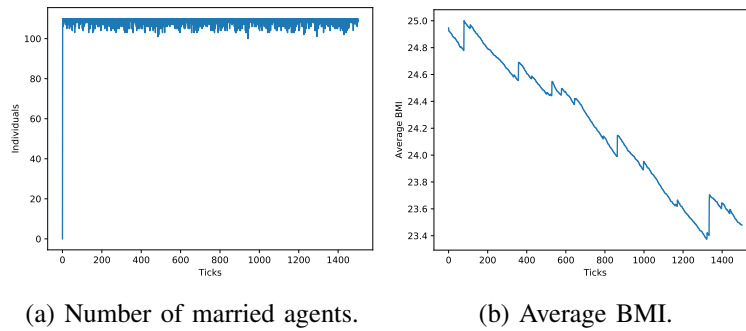


Figure 3: Results for radius of  $10^6$ .

In fig. 4 the results for the model with only one diabetic individual are presented. Clearly, the agent will change between the diagnoses, contrasting each other.

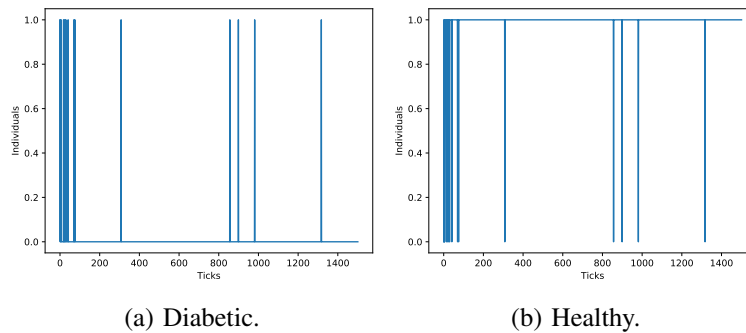


Figure 4: Results for one diabetic individual.

## 7 RESULTS

The following results were obtained simulating with ticks 1500, with initial healthy (71), risky (10) and diabetic (29).

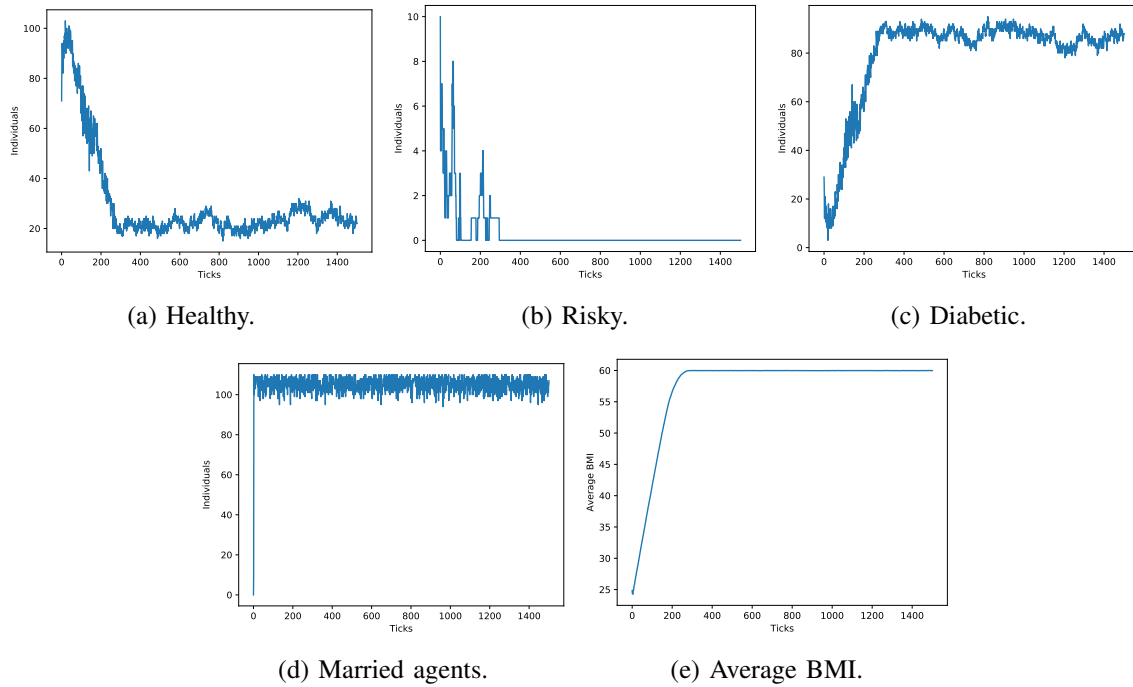


Figure 5: Results for one diabetic individual.

The results are presented in fig. 5. In the simulation, initially, agents delay changing their marital status, however, when they start marrying, social pressure starts increasing and, consequently, they begin marrying more often. Additionally, as marriages have an incidence on the BMI level, it must increase as well. Similarly, the number of diabetic individuals has to increase, since the BMI influence it with certain probabilities. This fact directly implies that the number of risky and healthy individuals need to decrease.

## 8 SENSITIVITY ANALYSIS AND EXPERIMENTATION

The proposed sensitivity analysis consists of varying the radius  $d$  10% below and above its original value. In this case, we extracted the average number of diabetic agents in the last 300 ticks (steady-state) and it was plotted against the current radius in fig. 6. It can be observed that the output does not change drastically, therefore the model is not highly sensitive to the radius.

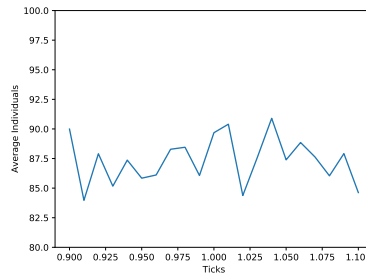


Figure 6: Sensitivity analysis.



## 9 CONCLUSIONS

The present work shows that the implemented model represents the dynamics of healthy, risky and diabetic populations, under the influence of social relationships through BMI variation.

Given that the diabetic population increases over time, we confirm the theories that affirm that diabetes is growing and can be considered as an emerging threat to public health.

As for future work, we propose that the decision rules can be reviewed formally. Additionally, we suggest that agents can learn and have a memory about their experience (previous states), for example, if an agent was diagnosed as diabetic in the past and it is currently recovered, it may have a large probability of eating constantly healthy.

## REFERENCES

- Altamirano, L. M. 2001. "Epidemiology and diabetes". *Revista de la Facultad de Medicina UNAM* 44 (1): 35–37.
- Atlas, D. 2015. "International diabetes federation". *IDF Diabetes Atlas, 7th edn. Brussels, Belgium: International Diabetes Federation.*
- Bays, H. E., R. Chapman, S. Grandy, and S. I. Group. 2007. "The relationship of body mass index to diabetes mellitus, hypertension and dyslipidaemia: comparison of data from two national surveys". *International journal of clinical practice* 61 (5): 737–747.
- Billari, F. C., A. Prskawetz, B. A. Diaz, and T. Fent. 2007. "The "wedding-ring" an agent-based marriage model based on social interaction". *Demographic research* 17:59–82.
- Devin Bowes 2019. "BDE". <http://ccl.northwestern.edu/netlogo/models/community/BDE702.T2DM2> [Online].
- Dubovi, I., and V. R. Lee. 2019. "Instructional support for learning with agent-based simulations: A tale of vicarious and guided exploration learning approaches". *Computers & Education* 142:103644.
- Jeffery, R. W., and A. M. Rick. 2002. "Cross-sectional and longitudinal associations between body mass index and marriage-related factors". *Obesity Research* 10 (8): 809–815.
- Kahn, B. B., and J. S. Flier. 2000, 8. "Obesity and insulin resistance". *The Journal of Clinical Investigation* 106 (4): 473–481.
- Martínez, I. V., M. E. Hernando, E. J. Gómez, R. Villares, and M. Mellado. 2012. "Definition of an agent-based model of the autoimmune response in Type 1 diabetes". In *7th Iberian Conference on Information Systems and Technologies (CISTI 2012)*, 1–4. IEEE.
- Montagna, S., and A. Omicini. 2017. "Agent-based modeling for the self-management of chronic diseases: An exploratory study". *Simulation* 93 (9): 781–793.
- Nejad, S. G., R. Martens, and R. Paranjape. 2008. "An agent-based diabetic patient simulation". In *KES International Symposium on Agent and Multi-Agent Systems: Technologies and Applications*, 832–841. Springer.
- World Health Organization 2019a. "Diabetes". <https://www.who.int/health-topics/diabetes> [Online].
- World Health Organization 2019b. "Obesity". <https://www.who.int/topics/obesity/en/> [Online].