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Modeling the influence of social networks and environment on energy balance and obesity

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ABSTRACT

The influence of social networks on the development of obesity has been demonstrated, and several models have been proposed. However, these models are limited since they consider obesity as a 'contagious' phenomenon that can be caught if most social contacts are deemed obese. Furthermore, social networks were proposed as a means to mitigate the obesity epidemic, but the interaction of social networks with environmental factors could not yet be explored as it was not accounted for in the current models. We propose a new model of obesity to face these limitations. In our model, individuals influence each other with respect to food intake and physical activity, which may lead to changes depending on the environment, and will impact energy balance and weight. We illustrate the potential of our model via two questions: could we focus on social networks and neglect environmental sources of influence, at least from a modelling viewpoint? Are some social structures less prone to be influenced by their environment? We performed a factorial analysis based on both synthetic and real-world social networks, and found that the environment was a key component behind changes in weight but its contribution was mitigated by structural properties of the population. Furthermore, the contribution of the environment was not dictated by macro-level properties (small-world and scale-free), which suggests that particular patterns of social ties at the micro-level are involved in making populations more resilient to change and less influenced by the environment.

1. Introduction

Increasing evidence has shown that the health of individuals is connected [38], which can be intuitively understood as friends who share activities such as dieting or exercising will also share a part of their health outcome. This was illustrated in a recent review by Hammond who found social influence to be a significant factor in obesity [33]. This review concluded that we need to better understand the interplay of social influences with other factors driving obesity, and that computational simulation represent "one especially promising approach" to help foster our understanding. In this paper, we propose a computational model to investigate the interplay of social and environmental influences.

Several computational models have been proposed to understand the role of social influence in obesity [4,35]. However, they only took a simplistic approach by considering that individuals directly spread their weight (*e.g.*, if one person has a majority of obese friends then he would simply turn obese). In this paper, we propose a new model of obesity, motivated by the fact that obesity results from a long-term imbalance between physical activity and food intake, and that these two factors are influenced by peers [8,11,22,39]. In our model, individuals are not directly acting on others' weights but rather influencing social norms regarding food and physical activity, which contribute to changes in weight. Furthermore, our model accounts for the fact that one is not only influenced by peers when making a decision about an activity such as exercising: the environment shapes the possible choices. This includes the physical (built) environment, which may limit the offer of places to exercise, and the norms conveyed by the media which contribute to decision making.

Bahr et al. concluded from their model that traditional interventions may fail because they do not take into account the impact of social networks [4]. This raises questions: could we focus on social networks and neglect environmental sources of influence, at least from a modelling viewpoint? Are some social structures less prone to be influenced by their environment? We illustrate the potential of our model by using it to investigate these questions, both for synthetic populations and a real-world population.

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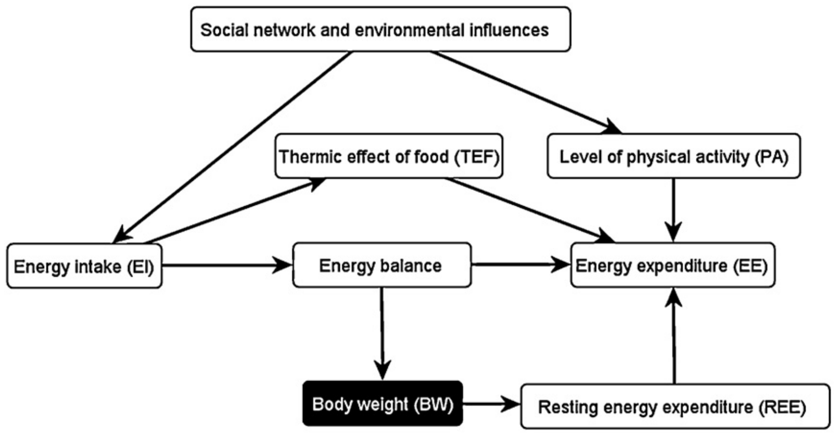

Fig. 1. Core model relationships. Social network and environmental factors are modeled as influencing energy intake and the level of physical activity. Energy expenditure is the sum of the thermic effect of food, resting energy expenditure, and the level of physical activity. Energy intake and energy expenditure determine the energy balance which in turn determines body weight.

1.1. Contribution of the paper

The principal contributions of the present work can be summarized as follows:

- We developed a model of obesity that accounts for social and environmental influences on food and physical activity, instead of a majority vote directly determining obesity as in previous models.
- We applied the model to investigate the relative contributions of social and environmental influences on the obesity epidemic, both for synthetic populations generated using known features of social networks (small-world and scale-free) and a real-world network.
- Our results suggest that the environment cannot be neglected, but its importance depends on the connections between individuals. In other words, the social ties of friendship are structured in different ways across populations, and these structures affect the sensitivity of a population to its environment. Some populations can be more cohesive, leading to a lower change on weight and being less prone to change based on the environment. The cohesiveness of a population is not a simple function of its high-level properties but may depend on structural features that remain to be investigated.

1.2. Organization of the paper

In Section 2, we focus on the processes unfolding on social networks: how individuals influence each other regarding food and physical activity. The principles of our model are first introduced intuitively, and then the mathematical specification is developed. In Section 3, we turn to using this process on social networks, both synthetically generated and extracted from a real-world sociological study. The motivating question is to investigate the contributions of social and environmental influences to obesity, that is, by monitoring changes on average weight. For both cases, we derive from a literature review representative values for initial weight, and we use previous research to assign values for initial physical activity. In synthetic populations, we explain how individuals are connected, and we detail the procedure that assigns meaningful values to the model's parameters in order to perform a factorial design (*i.e.*, identify the contribution of different influences). The same design is applied to a real-world population, and we compare the contribution of social and environmental influences in these different settings. Finally, we discuss the limitations of this model, due in part to gaps in our current understanding of obesity.

2. Model

2.1. Informal description

At the level of the individual, we explicitly model the main components of metabolism, as shown in Fig. 1. Whether an individual gains or loses weight depends on the balance between energy intake (*EI*) and energy expenditure (*EE*). When this balance (*EI*–*EE*) is positive, the energy surplus leads to an increase in body weight (*BW*). Similarly, if the balance is negative, then there is a loss in body weight. Energy expenditure is modeled as a function of three components: an individual's level of physical activity (*PA*), his resting energy expenditure (*REE*) and the thermic effect of food (*TEF*). *REE* is a function of the percentage of lean and fat mass which we approximated as a fixed percentage of body weight. *TEF* was assumed to be 10% of EI [14] and *PA* contributes to the calculation of energy expenditure as a multiplier of resting energy expenditure.

Both *EI* and *PA* in an individual are influenced by a combination of social network and environmental factors. The social network influence on an individual's physical activity or energy intake is the sum of the difference between the individual and each of his friends, normalized by the total number of friends. The social network influence is then combined with the influence of the environment, and if the resulting influence is sufficient (*i.e.*, above a set threshold), then an impact is exerted upon the individual (Fig. 2). The mechanism of a threshold and a corresponding impact models a simple decision-making process. If the model of an individual's action was to also include beliefs and previous experience, then an agent-based framework should be employed in lieu of the network framework used here. However, data may be currently too limited to allow for a richer decision-making process, as outlined in the Discussion. The mechanism proposed here aims at capturing a broad array of situations found in real-life, as exemplified in the following case.

If an individual who is not physically active is surrounded by active friends, then the influence of his social network will be great. If the individual also lives in an environment that promotes physical activity, then the combined influence of the individual's social network and environment is likely sufficient to trigger an impact on physical activity. However, the environment may also inhibit physical activity in which case the threshold may not been reached and the individual's level of physical activity remains unchanged.

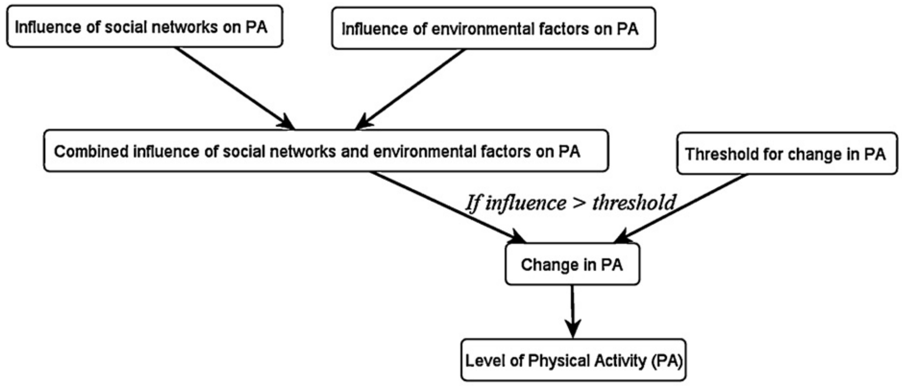

Fig. 2. Details of the social network and environmental influences on physical activity. All individuals in the model are considered to be in the same environment. The influence of one's social network is combined with the effects of the environment. The combined influence is compared to the threshold for a change in physical activity to determine if there is an impact on physical activity and the direction of that impact. Social network and environmental influences on energy intake are modeled in a similar fashion.

If a change in physical activity is triggered, then the individual's physical activity is changed by a fixed percent of his prior level.

2.2. Mathematical specification

2.2.1. Calculation of energy expenditure and energy intake

The energy expenditure of an individual i at time t, denoted $EE_i(t)$, involves three components. Firstly, the resting energy expenditure $REE_i(t)$, also called 'resting' or 'basal' metabolic rate, sustains the basic functions of the body. Secondly, the effect of physical activity $PA_i(t)$ is the energy used for muscular work and is calculated as a multiplier of $REE_i(t)$. Thirdly, the thermic effect of food $TEF_i(t)$, also called 'meal-induced thermogensis', is the energy used to process food intake. In the following, we use a simplified notation for the equations in which the individual i and the time t are omitted but apply to all variables.

To calculate resting energy expenditure, we use an empirical expression by Westerterp and colleagues based on multiple regression analysis over combined studies on adult healthy subjects [41]. This expression is provided as a function of lean body mass (LM) and fat mass (FM) [1,41]:

$$REE(\mathrm{MJ/d}) = (0.102 \times LM) + (0.024 \times FM) + 0.85 \quad (1)$$

Although lean and fat mass vary as a function of the body weight BW, we have used an approximation of fat mass as 25% of BW which is intermediate between 28% [26] and 21.5% [13]. This allows us to simplify the calculation of REE to:

$$REE(\mathrm{MJ/d}) = (0.102 \times 0.75 \times BW) + (0.024 \times 0.25 \times BW) + 0.85 \quad (2)$$

hence

$$\boxed{REE(MJ/d) = 0.083 \times BW + 0.85} \quad (3)$$

Although the thermic effect of food $TEF_i(t)$ depends on dietary composition, it is commonly approximated as 10% of the total caloric intake [14]. Thus total energy expenditure EE is calculated as:

$$\boxed{EE(MJ/d) = PA * (0.083 * BW + 0.85) + 0.1 * EI} \quad (4)$$

We consider that all individuals are initially in an equilibrium state, *i.e.*, they are not currently gaining or losing weight. In other words, before applying any socio-environmental factor, we consider that an individual is at steady state, therefore $EI_i = EE_i$ for all individuals i. By replacing EE with the formula above, we obtain EI:

$$EI(MJ/d) = PA \times (0.083 \times BW + 0.85) + 0.1 \times EI \quad (5)$$

thus

$$\boxed{EI(MJ/d) = PA * (0.083 * BW + 0.85)/0.9} \quad (6)$$

Initially, a value of PA and BW is assigned to all individuals (as will be detailed in Section 3.1). These values are combined to obtain the energy expenditure, which is then used to set the energy intake. Our formulas for the energy intake resulted in values from 6.3 MJ/d to 21.25 MJ/d, which is considered to be realistic [21].

2.2.2. Socio-environmental influences and their impact on the individual

The notation that we introduce for socio-environmental factors is summarized in Table 1. The impact of external influences on $EI_i(t)$ and $PA_i(t)$ is modeled in a 3 step process: we first compute the total influence exerted on an individual by his friends, then we combine this influence with the environment, and a change happens when the value is beyond a given threshold (Fig. 2). We start by computing the influence exerted on an individual i at time t by his friends, with respect to physical activity $PA_i(t)$ and energy intake $EI_i(t)$. We denote the set of all friends of i by F_i, and the number of friends of i by $|F_i|$. The influence is computed as the sum of the differences between the individual's feature and each of his friends at time $t-1$, weighted by the total number of friends. The weight is used to account for the fact that the influence is the result of the trend amongst friends, which is independent of the number of friends. In the absence of this weighting mechanism, individuals would become increasingly prone to changing behaviour as the number of their friends increase, even with very small behavioural differences between an individual and his friends. Thus, the total influence received from friends on

Table 1
Notation.

Symbol	Meaning
EI	Energy intake (MJ/d)
PA	Physical activity level (dimensionless)
I_{PA}	Impact on physical activity (dimensionless)
I_{EI}	Impact on energy intake (MJ/d)
Env	Environmental social influences (dimensionless)
T_{EI}	Threshold for change on energy intake (dimensionless)
T_{PA}	Threshold for change on physical activity (dimensionless)

physical activity and energy intake is given by the following equation:

$$\left\{\begin{aligned} Inf_{PA_i(t)} &= \frac{1}{|F_i|} \times \sum_{j\in F_i}(PA_j(t-1) - PA_i(t-1)) \\ Inf_{EI_i(t)} &= \frac{1}{|F_i|} \times \sum_{j\in F_i}(EI_j(t-1) - EI_i(t-1)) \end{aligned}\right\} \quad (7)$$

As we are interested in both social and environmental influences on i, we use a parameter Env to represent constant environmental influences from sources such as advertising, education, and the built environment. When Inf_{PA_i} is positive, then the individual is increasing his level of physical activity. Thus, a beneficial environment (Env) will further increase Inf_{PA_i}. On the other hand, a harmful environment will reduce the increase. To represent these two possible effects of the environment, we set it to be harmful when $0 < Env < 1$, and beneficial when $1 < Env < 2$. Thus, when Inf_{PA_i} is positive, the environment multiplies it. Similarly, when Inf_{PA_i} is negative, a harmful environment increases the result whereas a beneficial environment decreases it. This is summarized by the following:

$$\left\{\begin{array}{ll} \text{if } Inf_{PA_i(t)} \geq 0, & \text{then } Inf_{PA_i(t),Env} = Env \times Inf_{PA_i(t)} \\ \text{if } Inf_{PA_i(t)} < 0, & \text{then } Inf_{PA_i(t),Env} = \dfrac{Inf_{PA_i(t)}}{Env} \end{array}\right\} \quad (8)$$

The effect on the energy intake is the opposite, since positive values of the influence on energy intake are harmful instead of helpful as in the case of increased physical activity. Thus, the equations governing energy intake are:

$$\left\{\begin{array}{ll} \text{if } Inf_{EI_i(t)} \geq 0, & \text{then } Inf_{EI_i(t),Env} = \dfrac{Inf_{EI_i(t)}}{Env} \\ \text{if } Inf_{EI_i(t)} < 0, & \text{then } Inf_{EI_i(t),Env} = Env \times Inf_{EI_i(t)} \end{array}\right\} \quad (9)$$

If the socio-environmental influence on physical activity ($Inf_{PA_i(t),Env}$) or energy intake ($Inf_{EI_i(t),Env}$) is higher than a given threshold, then the corresponding value increases for the individual considered. If the influence is lower than the threshold, then the corresponding value decreases. The thresholds on energy expenditure and physical activity are denoted by $T_{EI} > 0$ and $T_{PA} > 0$, respectively. Similarly, the changes on energy expenditure and physical activity are denoted by $I_{EI} > 0$ and $I_{PA} > 0$, respectively. Taking energy intake as the example, the final equation for the socio-environmental impact and the possible changes in one unit of time is

$$\left\{\begin{array}{ll} \text{if } Inf_{EI_i(t),Env} \geq T_{EI} \times EI_i(t-1), & \text{then } EI_i(t) = EI_i(t-1) + I_{EI} \times EI_i(t-1) \\ \text{if } Inf_{EI_i(t),Env} < T_{EI} \times EI_i(t-1), & \text{then } EI_i(t) = EI_i(t-1) - I_{EI} \times EI_i(t-1) \end{array}\right\} \quad (10)$$

The equation regarding physical activity is the same, using the threshold T_{PA} and impact I_{PA}. Note that these thresholds are independent of the individual or time: they remain the same and hold for the overall populations.

2.2.3. Transforming energy into weight

Once an individual i has been influenced, we compute his current energy surplus $\Delta_i(t)$ by

$$\Delta_i(t) = EI_i(t) - EE_i(t) \quad (11)$$

There are several approaches to turn the energy surplus into weight. Two are considered in this paper, based on models from [10,20,41]. In a first scenario (A), we consider a fixed energy density of 32.2 MJ/kg. In other words, if $\Delta_i(t) = 32.2$ then the individual gains one kilo. This scenario is a suitable approximation for individuals having an initial body fat above 30 kg, but not for other individuals [20]. Furthermore, this scenario can lead to a large over-approximation. For example, eating 12 extra grams of butter per day results in a surplus of 0.4 MJ (or 100 kcal), for which

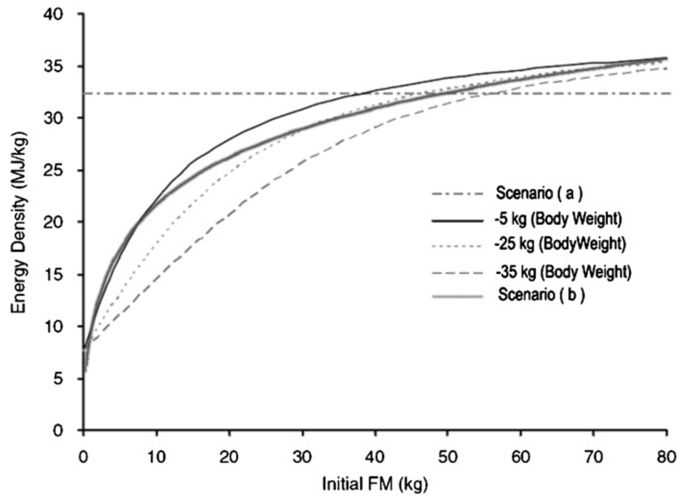

Fig. 3. The curves from Hall [20] were fitted with our interpolation, in bold and grey, for a scenario taking into account non-linear effects. The scenario that does not take into account the initial fat mass is a constant.

the scenario would predict an increase of 5.5 kg in a year. To provide more realistic predictions, a second scenario (B) considers non-linear effects. Indeed, it is known that the energy deficit required per unit weight loss grows with the initial body fat: obese individuals require a greater deficit in energy to lose the same amount of weight as lean individuals. As shown in Fig. 3, we fitted the typical curves from [20] by considering that losing 1 kg for an individual having an initial body fat x requires $f(x) = 7 \times \ln(x+1) + 5$ MJ. For example, an individual with 30 kg of body fat requires 29.03 MJ per kilo, whereas an individual with 15 kg of body fat requires 24.40 MJ per kilo. The results shown in this paper are based on experiments conducted for scenario (A). Scenario (B) did not result in a statistically significant difference.

3. Applications

3.1. Initial values

Initially, each individual is assigned a *weight* drawn from a normal distribution. To estimate the parameters of the distribution, we conducted a review of the demographic characteristics found in several cohorts, summarized in Table 2. We used the mean weight of 77.1 kg and the standard deviation of 15.675 kg from the Heritage Family study [26] because this was representative of the studies examined [13,21,32,41]. We also allowed for the broadest possible range of body weights of 38 kg up to 215 kg [41]. Randomly generated weights outside this range were discarded and new weight was generated.

Similarly, the *level of daily physical activity* (PA) is drawn from a normal distribution. The mean value is set at 1.53, which represents the level for a sedentary individual [15]. We used a standard deviation of 0.1 to reflect the fact that most people are sedentary [7]. As with body weight we allowed for a broader range of physical activity (1.4–4.7) based on data from the Food and Agriculture Organization [15].

Once an individual has been assigned a weight and a level of physical activity, energy expenditure is computed. Then, *energy intake* is set equal to energy expenditure in order for the individual to be initially at equilibrium.

Table 2
Literature review to provide initial conditions. When a cohort was divided into sub-populations, either by sex or by race, the mean and standard deviation reported in the table were obtained by a weighted average across sub-populations. The reported range was obtained by taking the combining the ranges given for each sub-population.

Feature	Stat. type	Values by reference				
		[21]	[26]	[41]	[13]	[32]
Weight (kg)	Range			[38,215]	[63.9,103.4]	
	Mean		77.1	71	81.5	77.4
	Std		15.675	20	10.29	17.8
Body Fat	Range	See note.[a]		[2,128]kg	[9.8,43.3]%	
	Mean		28%	19kg	21.5%	25.05kg
	Std		8.75%	14.5kg	7.35%	9.9kg
Energy intake (MJ/d)	Range	[4.09,22.10]			[10.89,16.75]	[2.96,18.26]
	Mean	8.02			13.19	8.668
	Std	2.32			1.76	2.32
Age	Range	[30,59]	[17,65]	[19,95]	[27,65]	[18,55]
Study origin	Country	US (Louisiana)	US and Canada[b]	Netherlands	US (Beltsville)	Canada
	Year	’99–’02	’02	’93	’02	’04–’06

[a] While there was no information about weight, the BMI indicated that 40% of the sample was obese, and this higher than normal result may come from a mean age of 48 years.
[b] Arizona, Indiana, Minnesota, Quebec, Texas.

3.2. Theoretical networks

3.2.1. Calibrating networks

The set of social actors (*i.e.*, individuals) and the links between them represents a social network. Determining an appropriate structure consists of deciding how individuals are connected. We consider that the social network always expresses the *small-world property* [36]. Informally, this property requires (1) that individuals often belong to communities, and (2) that going from one community to the other requires a small set of intermediate individuals [17]. Formally, the first requirement states that if an individual a is linked with b and b is linked to c, then a is also connected to c with high probability. To define formally the second requirement, let us denote by A the set of all social actors, N the number of actors, and dist(u, v) the distance between two actors u and v (*i.e.*, the minimal number of links to follow to go from one actor to the other). Then, the second requirement, known as a logarithmic average distance, corresponds to having an average distance in the order of the logarithm of the number of actors:

$$\frac{\sum_{u\in A}\sum_{v\in A} dist(u,v)}{N(N-1)} \propto \ln(N) \tag{12}$$

As the small-world property is often found in social networks, we assume that these two requirements always hold in our population. We also considered the scale-free property, which states that many individuals are linked to a few and a few are linked to many. This formally translates to having the distribution $p(x)$ of the percentage of individuals with x friends following a power-law:

$$p(x) = e^c \times x^{-\alpha} \tag{13}$$

We considered that, while the small-world property always holds, the *scale-free property* may or may not be present [17]. This resulted in using two network models. To represent a social network being only small-world, we use the model GP [17] (detailed in Fig. 4), and for a social network that is both small-world and scale-free we use the model H [5]. Since simulations were performed on both networks, they had to be comparable: they must be of similar size (*i.e.*, number of actors), and similar average number of friends per individual. Using the notation from [17], we use the instance $GP_{n=185,\delta=11}$ with 2405 individuals and 11.02 friends on average, and the instance $H_{n=7,t=4}$ with 2401 individuals and 11.57 friends on average. Both instances satisfy the small-world property. The first requirement, stating that the average distance should be in the order of the logarithm of the number of actors, is verified since we have 9.10 in $GP_{n=185,\delta=11}$, 3 in $H_{n=7,t=4}$, and $\ln(2400) \approx 7.78$. We also took the additional care of having the same probability (89%) for the second requirement (*i.e.*, a clustering coefficient of 0.89). The distributions of clustering are shown in Fig. 5, while the insets represent the distributions of distances.

These network models and the mathematical specification described in the previous Section were implemented in Java for a platform dedicated to the study of networks, tested in several other projects [18,19].

3.2.2. Calibrating the socio-environmental process

The goal of our analysis was to identify the contribution of social and environmental influences to the average change in weight of a population. The environmental influence was modeled as a single factor (*Env*), while social influences were further detailed into five factors: the quantity of influence required to trigger an impact on physical activity (T_{PA}) or energy intake (T_{EI}), the associated impacts on physical activity (I_{PA}) or energy intake (I_{EI}), and whether the population has a scale-free structure. In order to analyze the contribution of several factors, we used a *factorial analysis* [27]. In a factorial analysis, each experiment consists of a combination of values for all factors and all combinations must be tested. As we have 6 factors, if each of them can take k values then k^6 experiments should be performed, and possibly more due to replications. In order to keep the number of experiments feasible, we used a binary factorial design where each factor takes one high and one low value resulting in $2^6 = 64$ experiments. Each experiment is replicated four times, in order to account for variability due to different initial assignments of weight and physical activity.

Calibrating our model of socio-environmental process becomes a task of assigning meaningful high and low values for each factor. The values that were used in the factorial design are summarized in Table 3 and explained in the remainder of this section.

The high value for energy intake ($I_{EI,high}$ = 20%) was based on the literature on social facilitation of eating [8,11,24]. Studies which compared eating with friends to eating alone observed an increase in calorie intake ranging from 11 to 96% [6,11,24,9,29], and most studies suggest an increase of 40–50% [23]. We hypothesized that individuals are initially at equilibrium. Thus, they cannot be considered to be in one of the two extreme states (eating alone or eating with friends) and they are conceptually in an intermediate state which we took to be midway between 0 (alone) and 50% (with friends), *i.e.*, 25%. A high value of 50% is the same as 20% greater than the equilibrium value of 25% (for a variable x, $1.5x = 1.2 \times 1.25x$),

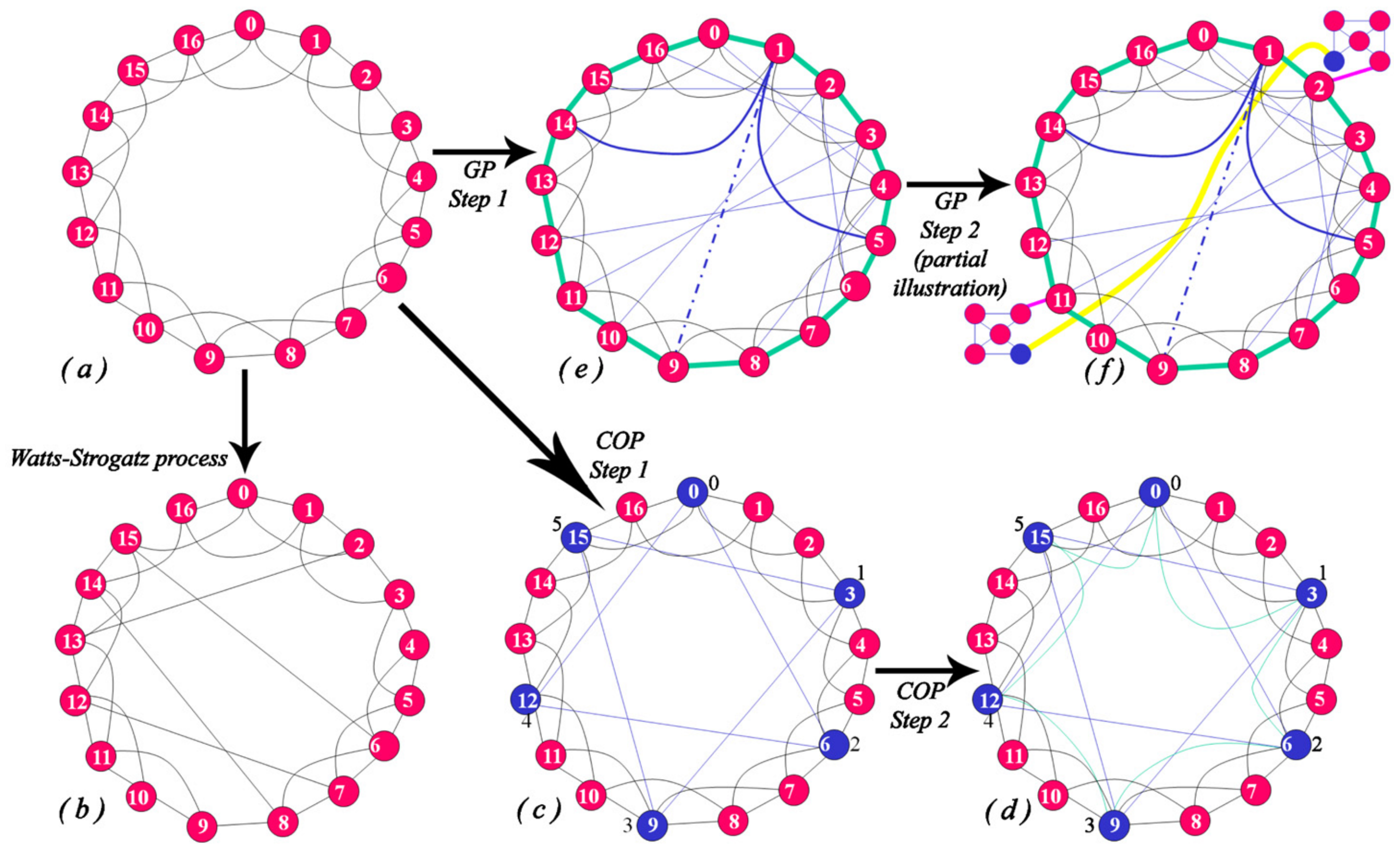

Fig. 4. A well-known small-world model is the Watts–Strogatz [40]. This model starts from a lattice of small dimension (a), for example in which each node i is connected to nodes $i \pm 1, i \pm 2, \cdots, i \pm \frac{\Delta}{2}$; in (a), $\Delta = 4$. Then, the 'signature' process of Watts–Strogatz rewires the endpoint of an edge with a small probability p (b). The model by Comellas, Ozon and Peters [12] uses the same base (a) but selects h equidistant nodes (c; in blue) and connects them using a double step graph; (c) shows the first step and (d) the second for a double step graph C(6,1,2). This model has higher clustering coefficient and lower average distance than Watts–Strogatz. The model GP further improves these values by considering that the base (a) has a good coverage of short-range links but that medium- and long-range links are not well represented by either Watts–Strogatz or COP [17]. Thus it connects each node i to $i \pm 2^0, \cdots, i \pm 2^k$ as long as $d(i) \neq \Delta$ (e; blue links). Then, it explicitely creates communities by adding a complete graph K_Δ to each node and rewiring one end to another complete graph (f; yellow link). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

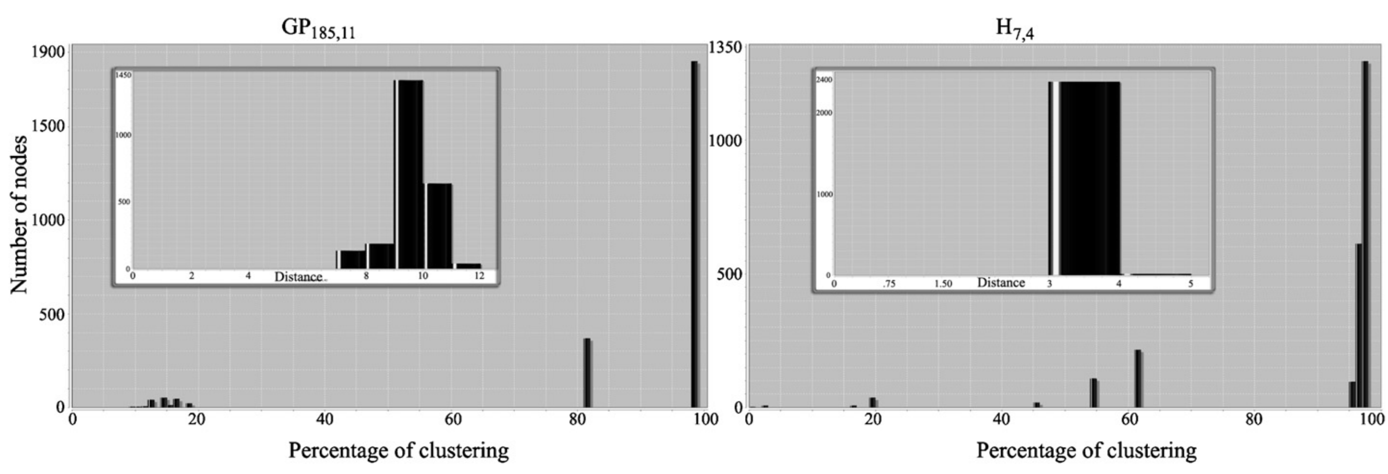

Fig. 5. Distributions of clustering and distances (insets) for $GP_{n=185,\delta=11}$ (left) and $H_{n=7,t=4}$ (right).

Table 3
High and low values used for each parameter in the factorial design.

Variable	Impact on physical activity (I_{PA})	Impact on energy intake (I_{EI})	Threshold on physical activity (T_{PA})	Threshold on energy intake (T_{EI})	Environmental influence (Env)
Low value	5%	5%	6%	6%	0.93
High value	20%	20%	6.5%	6.5%	1.02

Table 4
Selected experimental studies on social facilitation.

	References of experimental studies				
	[24]	[9]	[11]	[29]	[6]
Alone (kcal)	3861 kcal	435 kcal	375 kcal	742 kcal	1259 kcal
With friends (kcal)	4565 kcal	685 kcal	703 kcal	828 kcal	2469 kcal
Setting	Observed	Self-reported	Observed	Observed[a]	Observed
Place	United-Kingdom	US	Canada	US	US
Cohort age	28.3 ± 1.8	41.9 ± 13.7	21.9 ± 4		
Male/female	21/16	276/239	0/120	294/245	65/61

[a] Subjects were observed in 7 formal dining and 7 fast-food types of Fargo. No significant differences were found within restaurants of the same setting.

therefore the highest impact on energy intake used in the factorial design was 20%. The high value for physical activity was also set at 20% ($I_{PA,high}$ = 20%). We set the low value for the impact on energy intake and physical activity at 5%, one order of magnitude lower than the high value (5% = 0.1 × 50%) (Table 4).

No literature can currently inform our estimates for the threshold values of energy intake and physical activity (T_{EI} and T_{PA}). In other words, no sociological study was yet performed which would quantify in our model how much 'influence' someone needs to receive in order to change. Thus, we performed a simulation analysis to determine the parameter values that would give realistic changes in body weight. We simulated the average change in weight in the population by varying T_{PA} and T_{EI} together for all four combinations of I_{PA} and I_{EI} over 700 time steps, where a time step equals one day (Fig. 6). Social influences were exerted once per week to account for limited time devoted to social activities. Simulation results were compared to the changes in weight observed in the National Longitudinal Survey of Youth (NLSY79). This data set contains a nationally representative sample of 12,686 young men and women who reported their weight biennially from 1986 to 2004. The largest change between two successive reports was 3.6%, for women from 1990 to 1992. We selected $T_{PA,low} = T_{EI,low} = 6$, and $T_{PA,high} = T_{EI,high} = 6.5$ as they resulted in stable and realistic (<3.6%) changes in body weight. In a population that is both small-world and scale-free, we observed changes in average weight between −2.42 to 0% with a low threshold, and between −0.71 to −0.07% with a high threshold. If the population is only small-world, then the change ranges from −2.40 to 0.57% with a low threshold, and −0.69 to −0.11% with a high threshold. These values are consistent with the National Longitudinal Survey of Youth (NLSY79).

The behaviour of our system illustrated in Fig. 6 may, at first, seem surprising. However, it is theoretically common: this is a bistable system, depicting a very large unrealistic change followed by a transition that yields a small (realistic) change.[1] Such behaviour is common to a wide variety of systems, such as physical (water turning from ice to liquid at the tipping point of 0 °C) but more importantly cultural. For example, it was observed in a model representing individuals having independent cultural features, in which the connection between two individuals was more likely to be active if they shared more cultural features [28]. In our case, one suggested pratical explanation would be in analogy with noise: most influences are small, *i.e.*, there is a lot of small 'noises'. The threshold acts like a filter on noise: if it is set too low then the noises will distort the signal such that it produces unrealistic changes on average weight. However, there is a critical threshold at which most small noises are eliminated, leaving out the more realistically convincing influences, and leading to less fluctuation in the average weight.

We also confirmed that the behaviour of the system and the choice of threshold values does not depend on the size of the network. In other words, thresholds were scale-independent, as they held for larger networks such as $H_{5,4}$ with 625 individuals, $H_{6,4}$ with 1296 individuals, and $H_{8,4}$ with 4096 individuals.

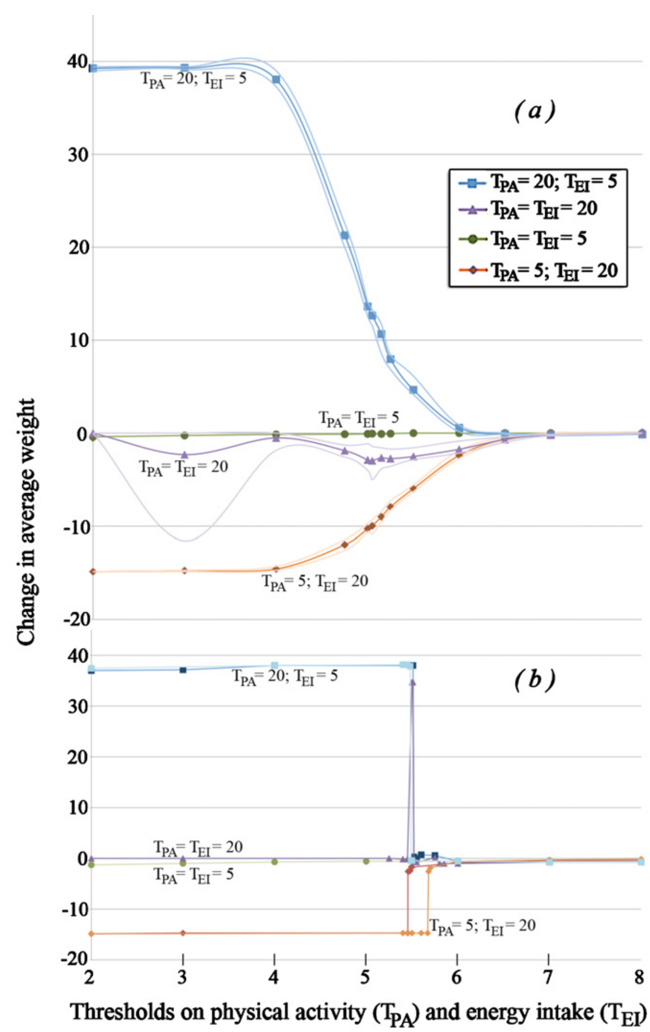

Fig. 6. Change on average weight for all combinations of impacts on physical activity and energy intake in a small-world network (a), and in a small-world and scale-free network (b). Data points in (a) are surrounded by max. and min. values. Two simulations are displayed for (b) due to a sharp transition. Realistic changes as determined from the NLSY79 dataset are given by values of T_{PA} and T_{EI} from 5.65 to 6.75.

[1] This happens directly when varying the control parameters T_{PA} and T_{EI} making this a first-order transition between the two states.

Table 5
Contribution of factors to the change in average weight.

	Environment	Topology	Social factors			
			I_{EI}	I_{PA}	T_{EI}	T_{PA}
Environment	**33.1**	9.2	5.8	7.0	0.9	2.5
Topology		**.4**	2.2	4.5	.8	1.6
I_{EI}			**4.8**	.0	2.8	.0
I_{PA}				**6.1**	.0	3.4
T_{EI}					**2.9**	0.0
T_{PA}						**3.3**

Finally, simulations were also used to identify the low and high values for the environment factor (Env). Calibration of the environment factor was based on the error rate for the factorial analysis for all combinations of the five other factors (thresholds, impacts, population topology) and for various values of Env. We selected the error rate that minimizes the sensitivity to initial conditions. For example, $Env_{low} = 0.97$ and $Env_{high} = 1.02$ results in an error of 18.43% in the factorial analysis, thus results would be highly sensitive to initial conditions and little could be concluded regarding the interplay of parameters. By selecting $Env_{low} = 0.93$ and $Env_{high} = 1.02$, we have an error rate of 8.7%. This small error rate allows for a comparison between the order of magnitudes of parameters.

3.2.3. Simulation results

We developed a mathematical model in which the food and physical activity behaviours of individuals are influenced by their peers. In this section, we focussed on designing a binary factorial design to investigate the contribution of socio-environmental features to the change in average weight of a *synthetic* population. Results are presented in Table 5. The diagonal shows, in bold, the contribution of single factors (known as primary effects). For instance, the table indicates that 6.1% of the change in weight is caused by how much individuals change their physical activity (I_{PA}). Cells above the diagonal provide the contribution of interacting factors, also known as secondary effects. A secondary effect is the contribution of two factors taken together, where one is given in the column heading and the other in the row heading. For example, the table shows that the contribution of the topology interacting with the impact of energy intake (I_{EI}) on weight change is 2.2%.

In synthetic networks, the environment plays a role as important as social factors. Alone, the environment explains one third of the change in average weight (33.1%), and an additional quarter (25.4%) through interactions (first line of Table 5) with factors such as the network topology (9.2%) and the changes in food and physical activity behaviours (sum of remaining interactions = 16.2%). Social factors, such as the threshold necessary to trigger a behavioural change (T_{PA}, T_{EI}) and the corresponding impact (I_{PA}, I_{EI}), explain less change by themselves (17.1%) but contribute to an additional third through interactions (31.5%). How individuals are connected (*i.e.*, the network topology) does not contribute in a statistically significant manner by itself (0.4%). Although it has a significant interaction with other factors (18.3%), half of it is due to the interplay with the environment (9.2%). These results suggest that, in the synthetic networks considered, social and environmental factors are of similar order of magnitude in explaining changes in weight of a population over time.

3.3. A real-world case

In the previous section, our simulations based on synthetic networks found that (i) the system is bistable with a sharp transition, and (ii) the environment impacts changes on weight to a similar extent as social factors. Was the bistability an artefact of the synthetic populations we generated, or is it a feature of our system? Is the impact of the environment similar in real-world populations or could different social structures mitigate it? To investigate these questions, we applied the same process on a real-world social network. In this network, the nodes are students from the University of California, and they are connected based on messages exchanged from April to October 2004. While the original network weights the connections by the number of messages or characters exchanged, our process assumes unweighted edges thus we considered whether a message was exchanged. This network was studied in Opsahl's PhD thesis [30] and is further described in [31]. This network has 1893 nodes, 13835 edges, an average distance of 3.055, and a clustering coefficient of 0.0568 [31]. The network is available online.[2] In the following, we will refer to this network as the 'student network'.

In the previous section, we determined the impacts on physical activity and diet from the literature. Due to a lack of data, the value of the thresholds on physical activity and diet as well as the environment were determined such that the population's average weight varies within a realistic range per the NLSY79 dataset and simulation errors are small. Thus, the values of thresholds and the environment are set *for a given population* and should not be seen as universal values holding in any populations. These values produced realistic changes in both the small-world/scale-free and purely small-world networks, but they may not yield satisfactory results in other networks. This was illustrated for the student network by performing a factorial design with replication, as in the previous Section. We used the same values for the thresholds on diet and physical activity, impacts on diet and physical activity, and environment. For each combination of values, the simulation was carried on 4 times, leading to $2^5 \times 4 = 128$ experiments. The final error was 54,71%, which demonstrates that these values are not meaningful for the student network.

Therefore, the student network had to undergo the same calibration process as in the previous section. When calibrating the thresholds' values, we noticed that the system was still bistable, as illustrated in Fig. 7 for one combination of values. However, the changes predicted by this real-world population were all within a realistic range, compared to the synthetic populations which had one unrealistic phase (up to a 40% increase on

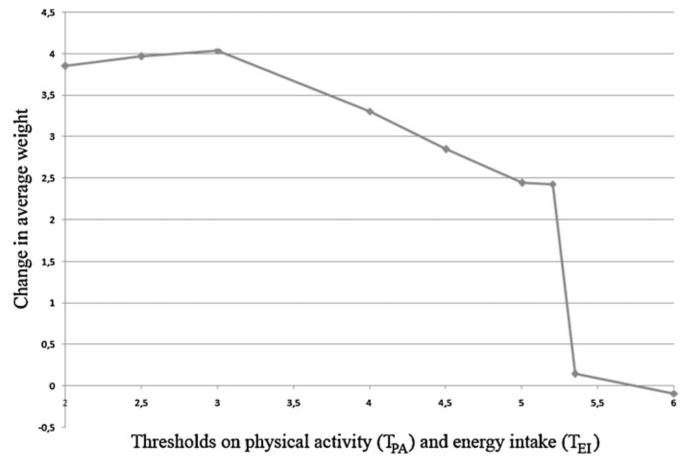

Fig. 7. A sharp transition is witnessed on the student network for $I_{PA} = 20$ and $I_{EI} = 5$.

[2] http://toreopsahl.com/datasets/

average weight) followed by a realistic phase. Thus, this population appears to be more resistant against strong changes. As representative values for the thresholds, we selected 4.5 and 5.5 which results in changes different by one order of magnitude (2.8% versus 0.28%). Note that the thresholds' values are relatively close to the ones selected for the synthetic populations (6% and 6.5%).

As in the previous section, values for the environment were selected to minimize errors, resulting in values of 0.90 and 1.02. Again, these values are close to the ones for synthetic populations (0.92 and 1.02). The error was 3.09%, compared to 54.71% if we used the same values as in synthetic populations. The results are interestingly different from those for synthetic populations. While the environment was previously as important as social factors, in the student network social factors are the leading contributors. The sole impacts on physical activity and diet directly account for two-thirds of the change (66.14%) whereas the environment directly accounts for 9.94 and 6.11% through interactions.

Overall, the student network (i) confirms the bistability of the system, but (ii) appears to be less prone to large changes and (iii) is less influenced by the environment. This suggests that network properties other than being small-world or scale-free play a strong role in creating strong populations that are resistant to change and outside influences.

4. Discussion

Previous studies have demonstrated the importance of social networks in the context of obesity [33,38]. Mathematical models have been used to analyze how social networks may contribute to the obesity epidemic [4,25,35]. However, these models considered that obesity was spreading directly from person to person, whereas we know that obesity is the outcome of a long term imbalance in energy intake and energy expenditure. In this paper, we improved on previous models by taking into consideration the factors that contribute to this imbalance: food and physical activity behaviours. These factors were incorporated by using approximations of human metabolism (Fig. 1). By going from obesity spreading directly to a spread of obesity based on the adoption of behaviours, we achieve an increased degree of realism. Furthermore, our mathematical model improves the model of Bahr et al. [4], which assigned to an individual the majority weight amongst his friends. In our model, influences were exerted continuously and were cumulative, causing changes only when a threshold quantity was received. This exhibits non-linear dynamics (Fig. 6), which were recently advocated to improve the realism of models [34]. However, the assumption of thresholds can be questioned, based on two theories.

Firstly, the metaphor of the “boiled frog” [2] suggests that an important issue with obesity is that its development is so slow over time that individuals often do not react. Secondly, the literature on life events [37] shows that self-motivated changes (*i.e.*, inspirational changes) are a minority, and that most behavioral changes are undertaken because of rare events which act as external stimuli. These theories, centered at the level of the individual rather than the group, highlight that the non-linear dynamics in obesity may not be due to the presence of thresholds over continuous influences, but to the occurrence of rare events that radically change individuals' behaviours. In a group, it is likely that a combination of *both* thresholds and rare events are at work, as individuals are influenced as well as they can be suddenly inspired for changing. However, estimates of the contribution of each in regards to behavioural changes are currently unknown, and have not been researched so far.

Several extensions are possible to improve this model. However, each comes with its own requirements for data, and numerous gaps exist. For example, if the necessary data becomes available, the model could be extended to take into account how the history of individuals affects their reactions to socio-environmental influences. Indeed, individuals tend to return to their highest historical weight status [3], but this has not yet been explained in the context of social networks. The main possible modelling improvement that could be achieved with currently available data is with respect to the description of metabolism, as we considered only an individual's weight and not the separation into lean mass and fat mass. Using such a distinction and the equations from [41,20,10], we can more accurately depict the course of individuals, and avoid misclassifying individuals with a large lean mass as being obese. However, only a minor gain would be expected in the model's accuracy, since for the average individual approximately 95% of the energy goes toward fat mass and 5% toward lean mass [41].

We have illustrated the potential of our model for both synthetic and real-world populations. Our application was limited by numerous data gaps. Indeed, our model is a better depiction than one in which body weight itself is “contagious” but as a consequence applying it requires more data. For example, data on the social facilitation of food consumption provided us with an estimate of how much more individuals eat when with friends: this is the change due to the social event, but estimating how much influence was necessary (*i.e.*, threshold values) to create this change remains a challenge. In this work, we addressed that gap by varying the missing values and selecting those leading to changes on weight deemed as reasonable compared to the NLSY79 data.

Our application examined the contribution of environmental versus social influences with respect to changes in weight. Our results on synthetic networks exhibiting a strong small-world and scale-free properties showed that the environment could be as important as social factors in determining changes in weight. However, a real-world network provided a different picture. Even if the system behaves similarly (*e.g.*, first order phase transition), the contributions of factors are different. In the real-world network, changes are much smaller and less prone to be influenced by the environment. This leads to two observations. Firstly, the environment should not be neglected as it can have a strong independent impact and systematically interacts with social influences. Secondly, and more importantly, micro-level structural properties, rather than macro-level (small-world, scale-free) can be key in shaping a cohesive population where environmental influences matter less.

To go further, it would be of particular interest to investigate which parts of the environment are more affected by the micro-level structure of the population. In our model, the environment is a single variable that abstracts myriad aspects, ranging from the built environment to the media. A rudimentary attempt in future models can consist of going from this single variable exerted on all individuals to a variable that is individual specific. A more ambitious enterprise is to view the built environment (*i.e.*, the man-made surroundings) also as a network: road segments are connected when they are reachable from one another, in the same way as individuals in a social network are connected when they know each other. This allows us to extend our mathematical model to encompass both social network and built environment: individuals in the social network exert their influences through characteristics such as physical activity behaviour, and segments of the built environment also exert an influence through the opportunities (or the lack thereof) that they provide for exercise. However, research has already shown that numerous gaps exist in accurately modelling the environment and the social network [16]. For example, we are aware of general properties regarding the structure of social networks, but we do not currently know how these properties change if only the social contacts living nearby are modelled.

5. Conclusion

Research has acknowledged the role that social networks play in the development of obesity [33,38]. However, current models remain limited to considering obesity as a "contagious" phenomenon that can be caught if most social contacts are obese [4]. We proposed a model that takes into account how individuals influence each other with respect to food and physical activity, and how they contribute to weight through approximations of human metabolism. Applying this model to synthetic and real-world populations showed that the environmental influence is also a key component behind changes in weight but its importance depends on structural properties of the population at the micro-level rather than the macro-level (*e.g.*, being small-world or scale-free).

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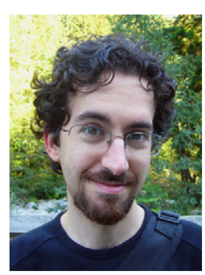

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