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The application of modeling and simulation to public health: Assessing the quality of Agent-Based Models for obesity

Philippe J. Giabbanelli [a,*], Boone Tison [b], James Keith [b]

[a] Department of Computer Science & Software Engineering, Miami University, Oxford OH 45056, USA
[b] Computer Science Department, Furman University, Greenville SC 29613, USA

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ABSTRACT

Early modeling and simulation models used in obesity research tended to be highly detailed on weight dynamics within the body or provided a very simplified view of socio-environmental influences by portraying obesity as a contagious disease (e.g., where weight directly 'spreads' among peers). The 2010's have witnessed the emergence of simulations for obesity as a new interdisciplinary field of research, leading to many articles in both health and simulation venues. Interdisciplinary teams have embarked on creating comprehensive models and, through the growing recognition of modeling as a powerful tool for public health, policymakers have been increasingly exposed to models that ought to support their decision-making processes. Several reviews have already documented how such models may be used in public health or how policymakers can be engaged in the model-building process. However, no systematic review has yet investigated whether the models were developed rigorously. We thus aim to address this gap by providing the first systematic review grounded in best practices for modeling and simulation. We investigate 32 Agent-Based Models developed between 2013 and 2019. This assessment effort is important to understand the extent to which these models can be trusted to support public health decisions. An assessment is also necessary to guide future developments in the field by identifying how the modeling and simulation community can address specific short- and long-term needs in improving Agent-Based Models of obesity for public health.

1. Introduction

The ongoing obesity crisis continues to be a significant health concern and an economic burden. The prevalence of obesity has almost tripled since 1975, with over 650 million adults living with obesity based on the latest numbers provided in [1]. Given the current trends, over 1 billion adults may be living with obesity within the next five years [2]. This prevalence and increase highlights the complexity of tackling overweight and obesity. Far from the oversimplification of 'eat less and move more', obesity emerges as the result of complex interactions between individuals and their environments. Modeling & Simulation (M&S) has emerged as one of the key methodologies in obesity research. The highly-cited physiological models developed in the 2000's and early 2010's help to predict the body weight loss associated with an obesity intervention [3,4]. Starting with the 2009 article of Bahr et al. [5], the nascent application of M&S to social norms helped to simulate whole-of-society effects of obesity interventions, ranging from regulations (e.g., zoning policy affecting the availability of fresh food products [6]) to peer effects [7]. The consequences of these interventions on body weight within the population are then estimated using earlier physiological models.

* Corresponding author.
E-mail addresses: giabbapj@miamioh.edu (P.J. Giabbanelli), boone.tison@furman.edu (B. Tison), james.keith@furman.edu (J. Keith).

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These simulation models allow policymakers and intervention design researchers to safely *identify* interventions with high potentials, since they are only tested in the virtual world afforded by the model rather than by directly impacting the target population [8]. The usefulness of such models has not gone unnoticed: for instance, public health state legislators in Georgia used a simulation model when passing a bill to promote physical activity [9]. Models also support the *evaluation* of an intervention [10,11], either by analyzing effects with respect to various parameters (e.g. with a Design of Experiments) or by examining when bottlenecks may occur throughout the course of the intervention. In addition to identification and evaluation of interventions, the M&S process also highlights where to focus the next *data collection efforts* [12], which is particularly useful in obesity research since this interdisciplinary field often needs to combine datasets on many factors [13]. It is thus clear that M&S provides essential decision-making tools to address the obesity crisis.

Given such societal responsibilities, it is essential to develop models of obesity in line with best practices and to identify limitations induced by factors such as model design or the supporting data. Such an assessment effort is a necessary step to guide the development of future models for obesity and continue to meet the demand of policymakers for "easy-to-use tools" that "enable decision-making in a timely manner" [14]. As shown in a recent thematic issue of M&S for population health [15], primary tools in the field generally include system dynamics, social network analysis, and agent-based modeling. In this paper, we focus on assessing Agent-Based Models (ABMs) of obesity, in which individuals are represented as agents which interact with each other and with their environment. ABMs are particularly relevant for public health problems such as obesity as they can support the social-ecological frameworks often used in this domain: individual traits are represented by attributes or characteristics of the agents, their relationships modeled via social ties "bridge individuals to their community and broader societal context", and ultimately agent-based models can represent how organizations and systems shape individual behaviors [16]. In short, the appeal of ABM comes from their ability to represent heterogeneity, individual interactions, and environmental mediators [6,17]. Despite this appeal, there are several concerns about whether the ABM methodology was applied soundly in obesity research. Recent analyses showed that an ABM of obesity could display unexpected behaviors [18] while another model appeared to make the same conclusions even when agents were modified to behave erratically [19]. Concerns have also been raised early on by obesity researchers on the difficulty of developing models without data [13], and more recently by policymakers who questioned the "quality and relevance of data used" in a model [20]. For instance, Tracy and colleagues noted that (emphasis added) "many public health-related ABMs estimate population health outcomes assuming that interventions had a certain level of effect (for example, reduced unhealthy eating by 10% or 20%), but *do not as of yet have sufficient data to simulate the steps of the intervention that would lead to such a reduction*" [21]. There is thus a pressing need to evaluate the technical quality of agent-based models of obesity for public health.

No study has yet been conducted to systematically assess these ABMs from a technical standpoint. This is not due to a paucity of studies: dozens of models have been created starting at the end of the 2000's. It is not due either to a lack of reviews, as no less than five reviews were written on this sole topic in the 2010's. The first systematic review of simulation models of obesity appeared in 2011 [22], followed by two reviews in 2015 [23,24], one in 2018 [25], and the latest review in mid-2019 [26]. The subject was also included in a 2013 review of systems approaches for childhood obesity [27], a 2016 narrative review [28], and a 2019 review of ABM for health behaviors (including weight-related behaviors) [29]. The absence of systematic technical assessment is due in part to the focus of existing reviews on explaining Agent-Based Models to obesity researchers, which leads to detailed descriptions with respect to applications [21] (e.g., individual physiology, social norms) while limiting the technical coverage to aspects such as the programming language used. The only study which examined the models from a technical standpoint was limited to 11 models developed between 2013 and 2016, which were manually chosen rather than identified through a systematic process [30]. In this paper, we address the evidence gap by providing a systematic technical assessment of recent agent-based models of obesity for public health. Our approach seeks to answer three specific questions:

(Q1) How soundly is each model constructed in terms of data handling, parameters, sensitivity analysis, validation, and potential reproducibility?
(Q2) Is the quality of models improving over time?
(Q3) Are modelers learning best practices from each other, as evidenced by citation patterns?

The remainder of this paper is organized as follows. To ensure that this application paper is self-contained, Section 2 situates agent-based models of obesity among other M&S methodologies and succinctly presents how they have been developed in this context. In Section 3, we explain our methods to systematically identify relevant agent-based models for obesity and analyze them. In Section 4, we present our key findings in tabular form based on 32 articles. Finally, these results are discussed in Section 5 together with short- and long-term recommendations to improve the quality of ABMs of obesity for public health.

2. Background

Different modeling approaches provide insights on different facets of a problem's complexity. Approaches can be broadly divided into three categories [31]: qualitative aggregate models, quantitative aggregate models, and individual oriented models. Models of obesity have been developed in each category. The Foresight Obesity Map is a qualitative model articulating how weight-related factors are connected, and it prompted conversations to understand who was responsible for which factors and how to achieve better coordination [32]. System Dynamics models, which belong to the category of quantitative aggregate models, have also been developed to help policy makers. For example, these models can be used as a virtual platform to test population health approaches [33], or can be a focal point to develop systems thinking capacity with regards to policies [34]. Fuzzy Cognitive Maps, which are also quantitative aggregate models, were created to help practitioners navigate the complexity of obesity in

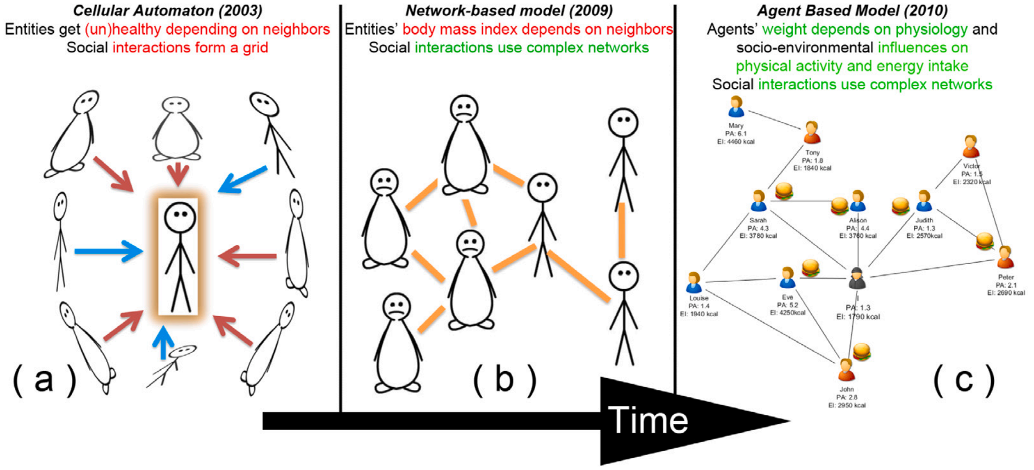

Fig. 1. Key milestones in the early development of individual based models from Rush [48] et al. (a) to Bahr et al. (b) [5] and Giabbanelli et al. (c) [49].

their patients [35]. Among individual oriented models, a large number of network-based and agent based models (ABMs) have been developed and suggested policy interventions; for example, readers can note markedly different ABMs as designed by Giabbanelli [36,37], Shoham [7,23], and Yang [38,39].

At a high level, an ABM can represent individuals, their interactions, and interactions with the environment. A consequence is that ABMs can represent the many sources of *heterogeneity* found in obesity: individuals have different characteristics, form decisions by using different processes, and live in places that differ in socioeconomic levels [38,40,41] or built environment, thus resulting in differences in exposure and access to healthy foods [42–44] or facilities for physical activity. Representing interactions and individual decision-making processes means that ABMs can account for the *feedback loops* that drive changes in weight [33,45]. These feedback loops (e.g., overeating leads to body shape concerns, which leads to stress that may trigger overeating) have stronger associations with obesity than the individual traits often evoked in popular (mis)conceptions of obesity, such as being impulsive [46]. An ABM is also a complex *adaptive system* as agents react to changing circumstances and may learn. The behavior of the overall system (i.e. the patterns of population health) emerges as the result of interactions between the agents and their environment, since individuals are influenced by their peers [47] and space with respect to both eating behaviors [37] and physical activity behaviors.

One of the earliest individual oriented models was developed by Rush and colleagues in 2003 who studied the spread of obesity as part of a course at the New England Complex Systems Institute [48]. This model used a cellular automaton, which assumes that the structure of social interactions among agents forms a grid. The environment was not represented and the update rules included turning an agent 'healthy' when most neighbors were healthy (Fig. 1a). The extreme assumption that people connect in a grid-like manner was questioned six years later by Bahr and colleagues who used networks, including but not limited to random ones and grids [5] (Fig. 1b). The environment was still missing and the rules continued to assume that an individual was likely to become obese if the peers were obese (through variations of a majority rule). This notion of obesity spreading as a contagious disease was motivated at that time by a high profile analysis from Christakis and Fowler, suggesting that weight gain spreads among people in the Framingham Heart Study [50]. The analysis was later shown to be erroneous [51] and the attention shifted to how *social influences* impacted weight [52]. It was in this context that we presented the first Agent-Based Model at the 2010 International Congress on Obesity [49], which included social influences on obesity through small-world and/or scale-free social networks as well as a physiological component to compute the weight gain (Fig. 1c). The model had an environmental variable (e.g. to study the effect of an obesogenic environment) but was not spatially explicit [36] (Fig. 1a). The early 2010s thus witnessed the emergence of ABMs that utilize all three aspects of this modeling approach: agents interact with the environment (which requires both aspects to be represented separately) and with each other (which requires a social network).

The lines of research and characteristics of ABMs for obesity began to fork in the 2010s. As summarized by Beheshti et al. three broad categories of ABMs for obesity emerged [17]: (1) spatially explicit models studying the role of the food and physical activity environment, (2) models focusing on the social network 'spread' of weight-related behaviors, and (3) models examining the diffusion of interventions. Although this category has the merit of simplifying the analysis, we note that studies may span multiple categories since networks function in space. That is, the complex problem of obesity is *both* a matter of geography and peer behaviors [53,54] since the social and built environment are both predictors of weight [55]. As an example of (1), agents in the 2014 model of Hammond and Ornstein either directly adjust their body mass index to match the mean of other agents, or indirectly change their body weight through adjustments in caloric intake or energy expenditure [56]. Many models for (2) were developed by Yang, Diez Roux and Auchincloss [39,41,57], often with a focus on physical activity. An example of (3) includes the extension of our model by Zhang and colleagues in 2014 to be spatially explicit by including the location and hence accessibility of stores selling fresh foods [58]. This extension has since been applied to numerous settings such as New York [59], San Antonio [60], or rural communities in West Texas [43].

Although all of these models contribute to some aspects of obesity research, the interdisciplinary nature of obesity means that the models can vary in terms of features: some represent eating behaviors and the location of food stores while others capture physical activity (e.g., walking, biking). While no feature is systematically present across all models, these models are united by the *absence* of certain features [19,42,61]. The social ties between agents are normally static in ABMs of human interactions, whereas they may appear or disappear in reality; all agents generally interact in a given time step, which is partly due to the large time steps considered (e.g., one time tick stands for one year); real-world mobility traces (e.g. GPS) are rarely used in simulating the exposure or utilization of various spatial resources; and agents are assumed to be perfectly aware of their peers' state (e.g., whether a peer engages in a healthy or unhealthy activity).

3. Methods

3.1. Identification of relevant articles

A key element of a comprehensive review is the search for relevant articles using a set of databases and/or academic search engines. Best practice is to use complementary search engines rather than a single one in order to provide sufficient coverage. Studies have shown that Google Scholar and PubMed are both strong engines but they have advantages and disadvantages which make them complementary [62]. A demonstration showed that *one* of two relevant studies may be found with each engine, but finding *both* studies requires using both engines [63]. We have thus used both engines for this review. Using each engine, we searched for "agent based model" *and* "obesity".

We did not set a restriction for the year so that we can estimate how many models exist, while noting that our analysis will focus on the more recent models (Section 3.3) to avoid making conclusions that are no longer relevant based on early proofs-of-concept. The abstract of each paper was independently read by two researchers with the following inclusion criteria:

(1) Is the article *about obesity*? Articles excluded at that stage are those focusing on other conditions (e.g., tobacco) and simply mentioning obesity (e.g., as an analogy).
(2) Is the article proposing a *new Agent Based Model*? Our objective is to assess the quality of ABMs, thus we perform the assessment when a model is *introduced* rather than in follow-up studies in which a model is *used*. For instance, the model of Zhang and colleagues [58] has been applied to numerous settings later on. If all later studies were counted despite using the same model, then this single design would have an excessive impact when making conclusion about ABMs in obesity.

There are two limitations to this search strategy. First, a consequence of criterion (2) was to exclude papers that combine Agent-Based Modeling with other modeling techniques. Although there has been a general growth in such hybrid models, particularly those linking ABM with Fuzzy Cognitive Maps [64], they are rarely designed for obesity [37]. In other words, simulation for obesity are predominantly done with a single technique (e.g., ABM, system dynamics [65], Markov models [66]) so hybrids are an exception rather than the norm [37,67]. We also note that assessment would be much more challenging if models were built on multiple techniques rather than one, since we would have to develop a rubric to assess other techniques as well as their combination. Second, a consequence of the keyword choice is that we cannot find papers which actually develop agent-based models without using that term. Waiving this limitation through additional keywords may lead to casting an excessively wide net in which other individual based models (i.e. network-based or cellular automata) would also be included and hence incorrectly assessed with criteria that do not apply to them. We note that this limitation primarily excludes the earliest ABMs as the terminology was not yet agreed upon (e.g., using *actor*-based rather than *agent*-based models [68]), and these models are not part of the time frame for analysis. We intentionally decided against including 'network' as a search term because that would also cover the active field of social network *analyses* in obesity [69] rather than *models*.

3.2. Elements to assess in each model

There cannot be a 'universal' ABM that supports any inquiry, as it would be as complex as the reality that it *necessarily* simplifies by virtue of being a model (hence the contradiction). The diversity of situations and questions in obesity research also prevents the 'automatic' generation of an ABM based on a few settings. Many aspects of a model are decided based on factors such as the needs of local policymakers, the skills of modelers, or the availability of data [70]. It would thus be extremely challenging to assess each model based on a checklist of what they should have done given their specific application context and resources. Consequently, many of our assessment items are devoted to knowing *what* choices were made and *why*. For instance, we cannot easily tell that 100 simulation runs are insufficient for a specific model, but we should know how many runs were made and a reason should be given for this number. Our assessment is thus based on the notion that modelers should provide sufficient *reporting* in their studies [71–73] ('what') and justify what makes their model *adequate* [74] ('why'). The assessment for each item is divided into three tiers (from T1 as 'best' to T3 as 'worst') which generally correspond to not knowing what was done (T3), knowing what but not the rationale or outcome (T2), and knowing why (T1). The exception from this categorization is the 'documentation and reproducibility' category in which items act as a checklist to count the number of aspects that were documented. Rather than holding models to our personal standards, we use *at least three references* to justify the aspects that a model should disclose and justify. The Assessment Sheet on our online repository at https://osf.io/n6pja/ exemplifies which models fall under T1, T2, or T3 for each of the items within each category.

We grouped items into five broad categories to facilitate the analysis. We study how ①**data** is given to, or generated by, a model (e.g., temporal resolution, number of runs). We examine how values are assigned to ②**parameters** and whether they are able to represent the heterogeneity that exists in obesity (e.g., by initializing agent characteristics based on distributions rather than constant values). ③**Sensitivity** looks at how outputs change based on either changes in parameter values or changes in model design. ④**Validation** examines how simulation outputs are compared to a reference dataset. Finally, ⑤**Documentation and Reproducibility** details the availability of artifacts such as code or documentation, based in part on the STRESS guidelines [73]. The remainder of this section details the items within each category.

3.2.1. Data (6 items)

Two aspects of a model deal with *time*: the temporal resolution, which is the physical equivalent of one time step in a model (e.g., one tick represents one day); and the total duration, such as 5 years. Modelers need to specify and explain the choices made for both temporal resolution and total duration [30,74,75]. Similarly, *space* includes the spatial resolution (e.g., is one cell 5 × 5 km? a house?) and the total space. Modelers should state how, and why, the environment is captured in a certain way [30,74–76]. The number of runs or *replications* is important to ensure that any aggregate (e.g., average output) is representative of the output's distribution [30,74,75]. *Agents' characteristics* is whether the attributes of the agents are clearly motivated by the need to capture the most salient features of their real-world counterparts [74,77,78]. For these four items, a model is categorized T3 when an item is unknown (e.g., cannot tell the spatial resolution) or ignored (e.g., no replications in a stochastic model); T2 if these choices are known but not justified (e.g., arbitrary round number of replications such as 100 or 1,000); and T1 when choices are justified.

When outputs of a model depend on a situation that may change (e.g., evolution of social norms but not physiological constants), then the data used to populate that aspect of the model should be sufficiently *recent* to ensure its relevance in the current policy context [74,76,79]. Data more than 10 years older than the model lead to its categorization as 'bad'; 5–10 years is 'decent'; within five years is 'good'. Finally, *data access* is important to be able to run a model or reproduce the authors' findings. Limitations happen when access is limited by legal restrictions or the data is confidential (e.g., private business data) [30,71,74]. A model is T3 if we do not know its data sources; T2 if we know the sources but cannot easily access them (e.g., payment or board approval is required); and T1 if the key data can be publicly accessed.

3.2.2. Parameters (2 items)

Parameters are not only created to offer policy levers when designing interventions (which is desirable for end-users), but also as *free parameters* which ensure that a model can run despite gaps in the theory or limited availability of data (which is less desirable). The latter should be minimized, in favor of values that are backed by evidence [72,76,79]. A T3 model uses too many parameters with arbitrary values. A T2 model details all free parameters, but does not justify all distributions or does not attempt to minimize the number of parameters (which a T1 model does). Finally, *heterogeneity* is supported when parameters draw from distributions fitted to data rather than using a single value [30,72,76]. A T3 model does not draw from distributions, a T2 does but does not show how distributions were fitted to data, and a T1 also covers the fitting process.

3.2.3. Sensitivity analysis (2 items)

The output of a model may be *sensitive to its input*, thus we need an exploration of the state space to understand this relation (e.g., through a factorial design) [30,72,76]. The output may also be *sensitive to changes in model design* (e.g., is the relation between obesity and stigma linear or logarithmic?) [30,74,76]. Neither aspects are examined in a T3 model. A T2 model assesses them but, unlike a T1, does not provide the results.

3.2.4. Validation (1 item)

The output of the model should be compared to real data, such as a real time series (that can be compared against the model's *simulated* time series) on the phenomenon being modeled or output from validated models with a similar application context [72,75,76,79]. A T3 model does not compare its outputs, a T2 does the comparison but results are unknown, and a T1 provides the results.

3.2.5. Documentation and reproducibility (18 items)

The documentation should describe or include [71–73]: the environment, its structure and initiation; the programming language/environment used; libraries used; hardware; a link to the source code; a documented source code. Researchers have also recommended [72–74] that the description should state the research objective for the model, list all agents and connections, define how agents are created, define how agents are destroyed, list and detail all data sources, and state how data is processed. Several articles have called for a diagram giving an overview of the model, a summary of the logic involved in the base model and scenarios, a list of algorithms involved, and a list of parameters describing each value used [72,73,76]. Finally, some have asked for a statement of background and rationale [72,73,75], or an overview of effects that emerge from agent interactions [72,73,79]. The three categories are: T3 (lower tier) for less than 6 items, T2 for less than 12, and T1 (top tier) for 12 and above.

Table 1
Assessment for the first four categories. There are 4 exceptions: space† was not applicable in 15 studies as it was not represented; data access• was not applicable in 6 studies because no data was used; one study had no free* parameters; and five studies ensured heterogeneity⊕ via individual level data rather than distributions.

Cat.	Item	T3 (worst)	T2	T1 (best)
Data	Time	18.8% (n=6)	28.1% (n=9)	53.1% (n=17)
	Runs	37.50% (n=12)	46.9% (n=15)	15.6% (n=5)
	Space†	3.1% (n=1)	3.1% (n=1)	46.9% (n=15)
	Agents' characteristics	0% (n=0)	100% (n=32)	0% (n=0)
	Recent data	3.1% (n=1)	46.9% (n=15)	50% (n=16)
	Data access•	12.5% (n=4)	9.4% (n=3)	59.4% (n=19)
Params.	Free*	9.4% (n=3)	34.4% (n=11)	53.1% (n=17)
	Heterogeneity⊕	6.3% (n=2)	31.3% (n=10)	46.9% (n=15)
Sensitivity analysis	To inputs	62.5% (n=20)	21.9% (n=7)	15.5% (n=5)
	Model design	50% (n=16)	6.3% (n=2)	43.8% (n=14)
Validation	Compare output	18.8% (n=6)	37.5% (n=12)	43.8% (n=14)

3.3. Assessment training and protocol

Each article was independently evaluated by two researchers who received training in simulation via one dedicated course. To ensure that they were confidently able to apply the guidelines to this corpus, a sample of the models was first read and categorized by a third (lead) researcher, then independently categorized by the two researchers. Upon completion of this sample, the two researchers compared their categories with each other and with the lead researcher, who also provided studies with highlights showing how categories were derived from specific parts of the articles. All researchers met to discuss and solve differences. The two researchers then independently read all articles in the corpus and compared their conclusions for each item of each article. Differences between the researchers were noted and reconciled. For transparency, these differences are listed in the Difference spreadsheet on our online repository at https://osf.io/n6pja/.

To make an assessment of ABMs in obesity based on current practices, we avoid including early developments in the field. The foundational model from 2009 [5] started with obesity being ‘contagious’ and the first article proposing a model with socio-environmental norms appeared in 2012 [36]. Consequently, our analysis starts with models published in 2013.

4. Results

The results from our search strategy (Section 3.1) are shown in Fig. 2. The distribution of articles over time is provided in Fig. 3, while noting the subset of articles used for assessment (Section 3.2–3.3). The individual articles underlying Fig. 3 are listed in the ArticlesGathered spreadsheet on our online repository at https://osf.io/n6pja/. The remainder of this section provides the data necessary to address our three guiding research questions, together with an analysis of the data.

Our first research question requires assessing each of the 32 models with respect to our 5 categories and their 29 items. The resulting assessment matrix is provided online in the Assessment spreadsheet while aggregate results in the first four categories are presented in Table 1 and organized in tiers. Results for documentation and reproducibility are presented in Table 2 as a checklist approach was used to assess the presence (or absence) of each item. The aggregate results from Tables 1–2 are also provided in our online spreadsheet ArticlesResult. Results on the quality of each model (Table 1) are mixed: several items are commonly addressed across models but many others appear to be lacking. On the positive side, most modelers explain and justify the spatio-temporal aspects of their models when applicable. Data is commonly a few years old and a large fraction of it can be publicly accessed. Models commonly support heterogeneity, which is one of the very reasons for the use of Agent-Based Models in obesity research. Alternative choices in model design are considered in half of the cases, with results provided most of the time. On the negative side, only 15.6% of these stochastic models provide results that are statistically representative of the model's behavior: 37.5% of the models do not perform multiple runs, while 46.9% perform an ad-hoc number of runs that may not have statistical power. Validation is another critical aspect of modeling, which is one of the fundamental requirements to demonstrate the quality of a model. Most studies (56.3%) do not provide any results for validation.

We find the results more encouraging in Table 2 when it comes to documentation. The background, rationale, and objective of each model was stated. This is important because it specifies the context of use for the models, thus contributing to preventing incorrect applications of a model due to a lack of information. In terms of agent specifications, we always know their environment (when applicable) and how they are created. Although the destruction of agents is almost never specified, these models do not normally seek to predict mortality and hence rarely have to dispose of agents. Indeed, they operate under the assumption of a closed population to predict how an intervention changes the prevalence of health indicators (e.g., cardiovascular issues, weight status) compared to a baseline or ‘status quo’ scenario. We also positively observe that data sources are frequently mentioned and that most models come with known parameter values. However, only 2 out of 32 articles provided their source code.

Our second research question on the possibility of methodological improvements over time is addressed through the time series shown in Fig. 4. We observe that the average number of T3 items (i.e. needing the most fixing) remains relatively constant over time. Although the number of T1 items trends upwards on several years, there is no statistically significant trend as evidenced

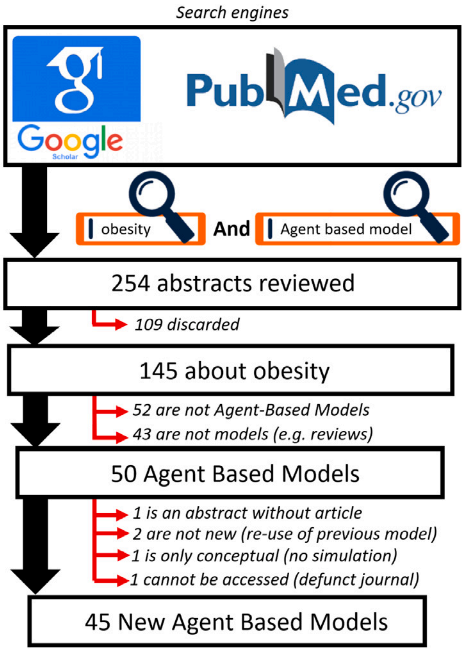

Fig. 2. Process resulting in 50 new obesity ABMs.

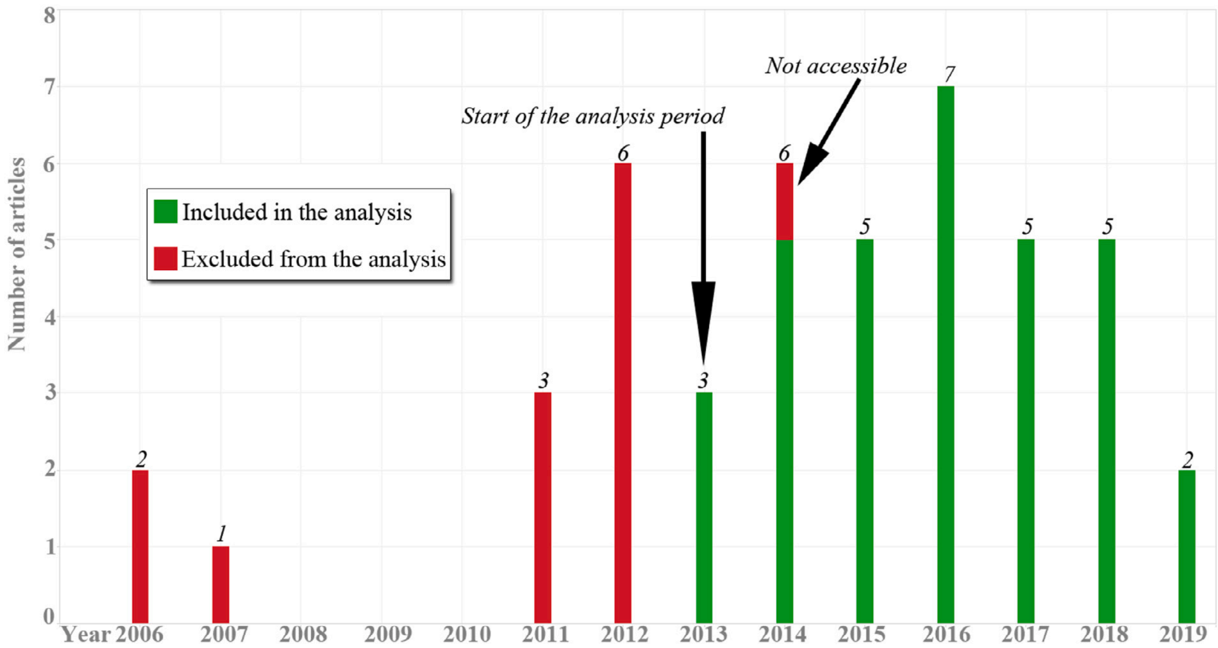

Fig. 3. Number of articles found in each year.

by a P-value of 0.73 and R^2 of 0.02 for a linear fit. Similarly, there is no statistically significant decreasing trend for T2 items given a P-value of 0.69 and R^2 of 0.03 for a linear fit. A complementary analysis through a one-way ANOVA found no statistically significant (i.e., P-value less than .05) differences in the scores for T1, T2, or T3 when articles were partitioned based on the median publication year (pre-2016, 2016 and later). We thus conclude that models are not getting significantly better over time, which suggests proliferation rather than progress.

The third research questions necessitates an investigation into citation patterns, which are shown in Fig. 5. The field of ABMs for obesity does not constitute one connected component as we note that several articles (Fig. 5 – bottom) were neither built on

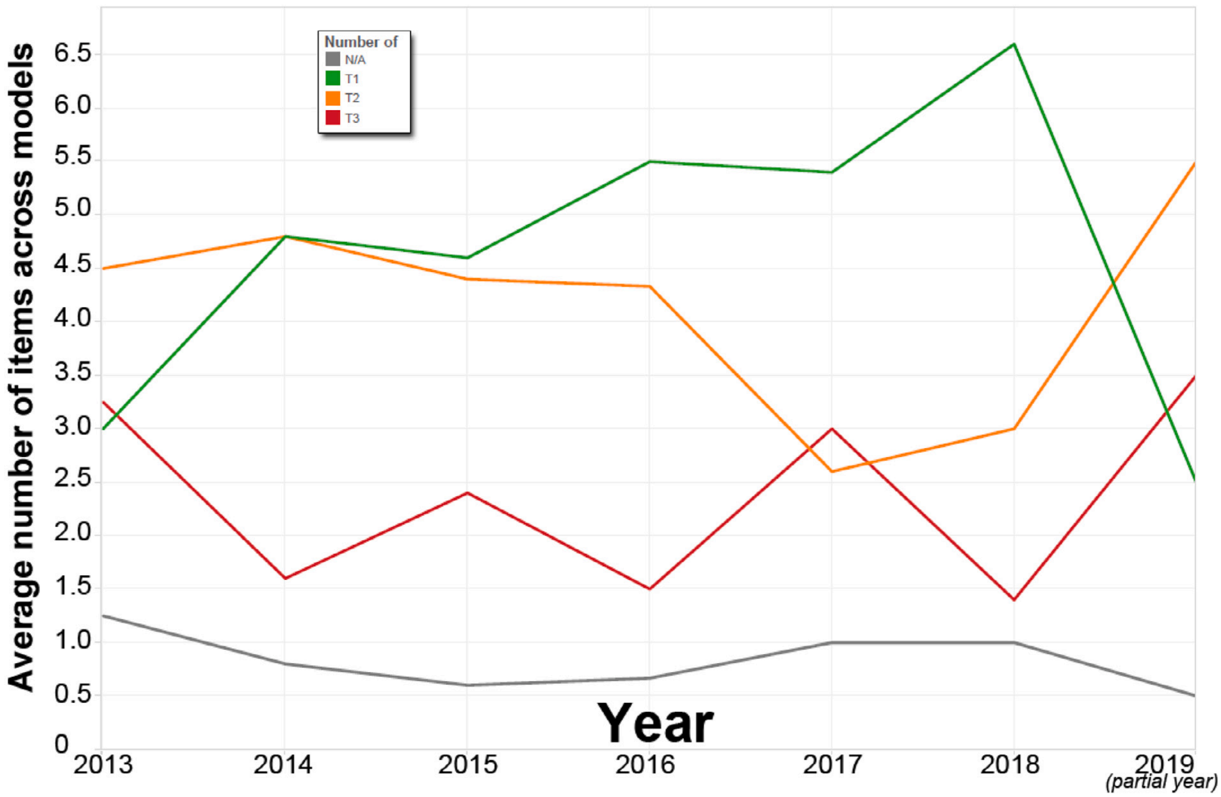

Fig. 4. Average numbers of items in each tier across articles per year of publication.

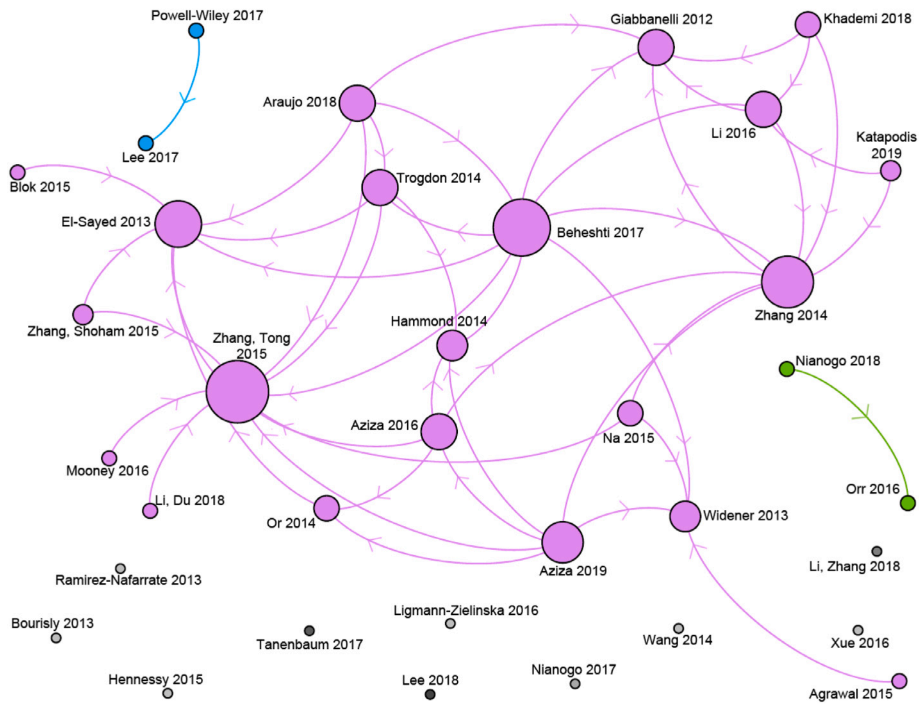

Fig. 5. Directed network of citations, in which an edge from an article *A* to *B* indicates that *A* cited *B*. Visualized with a force layout and expansion. Colors indicate connected components and node sizes are proportional to degree (i.e. total number of edges involving the node).

Table 2
Content of the documentation for each model. There were four exceptions: 6 studies had no agent interactions hence no emerging outputs†; 15 studies had no physical environment to describe •; 10 studies had no agent interactions to report*; and 13 studies used too short timelines for death⊕ to be meaningful.

Item	Present	Absent
Background and rationale	100% (n=32)	
Research objective	100% (n=32)	
Outputs emerging from agent's interactions†	81.3% (=26)	
Overview model diagram	53.1% (n=17)	46.9% (n=15)
Base model logic	100% (n=32)	
Algorithms used	46.9% (n=15)	53.2% (n=17)
Agents' environment•, its structure and initialization	53.1% (n=17)	
Agents' connections*	64.6% (n=21)	3.1% (n=1)
Agents' creation	100% (n=32)	
Agent's destruction⊕	9.4% (n=3)	50% (n=16)
Data sources	93.8% (n=30)	6.3% (n=2)
Data processing	43.8% (n=14)	56.3% (n=18)
Input parameter values	81.3% (n=26)	18.8% (n=6)
Programming language or environment used	65.6% (n=21)	34.4% (n=11)
Libraries used	46.9% (n=15)	53.1% (n=17)
Hardware used	9.4% (n=3)	90.6% (n=29)
Link to source code	6.3% (n=2)	93.8% (n=30)
Documentation of source code		100% (n=32)

earlier ones, nor were cited by later ones. This stands in contrast to other applications of M&S such as HIV research, in which models tend to provide incremental improvements upon one another through the addition of new states [80]. We also observe the presence of communities, with one in top-right formed of articles authored by Donglan Zhang and collaborators [6,36,43,58,59] and another in the bottom-left involving collaborators of David Shoham [81,82] or Abdul El-Sayed [83,84]. Few studies, such as Beheshti's [17], acknowledge work done across communities. In conclusion, citation patterns (Fig. 5) support the argument that a lack of improvement over time is due in part to focusing on familiar tools: several studies were not explicitly aware of any model recently developed by others. In several cases, when an article explicitly acknowledges the existence of a model (through a citation), it is a model developed within the same group of collaborators. Few studies provided a comprehensive perspective that looked at models created by different groups.

As two of our own works were included in this assessment, we examined whether the results showed any potential partiality and found no evidence of such bias. As can be seen in our supplementary material, our two works (listed under entries #16 and #33) were not the best during their time periods as others either had a higher T1 score or covered aspects that were not included in our model. Our two articles both include an item in category T3. We also note that the authors directly conducting the assessments (BT, JK) did not author any of the works reviewed.

5. Discussion and conclusion

Obesity is a prevalent and increasingly common condition [1,2] associated with adverse effects on individual health and costs for healthcare systems. Given the complexity of obesity, Modeling & Simulation provides tools for policymakers to identify and evaluate potential interventions. In this paper, we focus on Agent-Based Modeling, which is one of the primary M&S approaches used for population health [15]. Despite the many reviews on M&S models (or ABMs specifically) for obesity [22–26,29], none has so far assessed the technical soundness of the model building process. This assessment is essential to ensure that M&S is used rigorously in delivering tools that policymakers can trust and effectively use for their purpose. An assessment also lays the foundations on which to set realistic goals in improving the model building process for the next generation of obesity ABMs in the 2020's. Although assessments have regularly been conducted on simulation models of human behaviors, such as the landmark bibliography of 2,034 studies by Dutton and Starbuck in 1971 [85] or the analysis of 128 models by Angus and Hassani-Mahmooei in 2015, no technical assessment had yet been performed on ABMs for obesity. Our assessment is thus the first to examine 32 ABMs developed from 2013 to 2019 with respect to key items such as validation, replicability, or the use of data. Three questions guide our analysis: (1) how well does each model deal with critical aspects of the M&S process; (2) are models getting better; and (3) are modelers learning best practices from each other?

Although modelers commonly explain the spatio-temporal aspects of their model and adequately use agent-based models (e.g., to represent individual heterogeneity), three essential issues remain and will need to be addressed in the next generation of models.

First, issues of validity and a lack of replications are particularly concerning as they impact the extent to which we can use the models to support critical decision-making activities. For instance, several studies used no data, which makes it even more challenging to check the fidelity of the outputs (i.e. validation) or inputs (i.e. calibration). Second, there are several concerns surrounding data processing. In many studies, we do not know how existing data is transformed or provided to the model, although there are several important methodological choices such as the handling of outliers or missing values. We thus need to shift from the notion of a model as being solely 'simulation code' and realize that data processing is an integral component of the modeling effort. This paradigm shift is a challenging long-term transition, but it is a necessary step to support replication efforts and contribute to building trust in models that may be used to affect population health. Third, transparency and replicability are hindered by a general lack of access to the source code. Since providing code is almost a statistical anomaly, there is no code documentation either. Sharing the code and its documentation ought to be a relatively easy task given the abundance of third-party repositories that can be easily searched for ABMs [86], so the field already has the means to quickly make an improvement. Code sharing may also contribute to alleviating some of the other issues: teams versed in statistical methods can analyze how many runs are needed for an output to be in the desired confidence interval, or perform a sensitivity analysis based on Design of Experiments techniques. In a situation where models are relatively well documented and most of the data is publicly available, the code may be the missing link to achieve short-term methodological improvements.

Many of our conclusions echo previous assessments of ABM in general. The fact that the never given is not unique to obesity: Janssen reported that about 90% of studies do not release their code [87]. Angus and Hassani-Mahmooei also found that the number of replicates was often missing and that comparison to data was insufficient [88]. The main surprise is how little changes over time: Angus and Hassani-Mahmooei performed their assessment on models published between 2001 and 2012, while ours continues with models published between 2013 and 2019. Their concern that the ABM community "fail at practicing basic scientific hygiene when it comes to presenting its results" remains valid, and there is limited evidence of an "attempt to apply order by enforcing one or more standards" [88].

Since a common incentive to improve the design of a model is to address the feedback of reviewers, the lack of significant improvements over time may raise questions about the review process. However, a lack of rigor in the reviewing process is an unlikely culprit: many of the articles that we reviewed appeared in some of the most prestigious journals within the field of health, as evidence by the tier 1 journal categorization (Scimago Journal Rank) for 'American Journal of Preventive Medicine', 'American Journal of Epidemiology', 'Social Science and Medicine', or 'BMC Public Health'. A possibility is that reviewing applied M&S work faces intrinsic difficulties as its interdisciplinary nature requires reviewers familiar with the latest developments in M&S methodologies, reviewers with expertise in obesity, and reviewers able to operate at the interface between these fields. Another possibility is that the authors are not aware of all methodological developments which may improve their modeling process. This hypothesis was already verified in a previous analysis of the M&S literature in the context of participatory modeling, which found that "the prior experience and skills of the modelers had a dominant effect on the selection of the methods used" [70]. Our paper presents additional evidence for this hypothesis, through the patterns found in co-citation analysis, an established approach to explore the M&S literature [89,90]. There is thus a potential need to support the dissemination of best practices by supporting the development of research networks that go beyond established collaborations. Although there are established M&S research networks in broad domains such as infectious disease modeling (e.g., the MIDAS network) and in much narrower domain such as *childhood* obesity (e.g., the Envision project at the National Collaborative on Childhood Obesity Research), there is still a need to coordinate a network of researchers at the interface of M&S and obesity.

A regular assessment is a necessity to monitor and guide the development of a field. As such assessments are performed again in the future, we note that some of the items would need to be adjusted or even developed for three reasons. First, there are evolutions in techniques, and particularly in the use of hybrid ABM which has been relatively rare in obesity research [36,91] but may continue to grow as suggested by emerging practices in other fields [64,92]. These rare hybrid modeling studies were excluded from our review, but future assessments may develop additional rubrics to assess ognitive map of the psychosocial determinants the technique used together with ABM (e.g., technical soundness of a Fuzzy Cognitive Map or System Dynamics component) as well as how the techniques are combined. Second, as high-level issues get resolved, we can start to examine the details and thus gradually raise the bar on model quality. For instance, we assessed whether several items (e.g., spatio-temporal resolution, agents' characteristics) were described and justified. Since many studies do not include any justification, we could not judge the *quality* of the justification. If justifications are more routinely provided or even mandatory in the future, then the next assessment efforts will be able to examine these choices (e.g., was 'based on data' an evasive argument for a questionable choice?). Third, our understanding of obesity progresses, and thus our expectations for realism increase accordingly. There is evidence of assortative mixing (i.e. homophily) in the social networks of obesity: two individuals are more likely to be connected when they are in a similar weight category. However, a 2020 review concluded that the underlying mechanisms are still unclear [93]. ABMs are thus currently tools to *explore* such mechanisms [93,94], but once they are understood, the expectation will shift to *including* the right mechanisms in the next generation of models. It is thus particularly likely that the structure and function of social ties will grow to an assessment category of its own, including checks for the presence of requested properties (e.g., small-world, assortative mixing) and levels of quality on how a model represents changes in social ties over time (e.g., validation of the longitudinal sequence of ties).

Our study evaluated each ABM when it was initially proposed. Few ABMs have been continuously developed and expanded in follow-up studies. We excluded such extensions given their relative paucity and the risk of one 'line' of model dwarfing results from other models by being over-represented. The consequence of excluding models that *use* rather than *develop* ABM is that our study does not examine whether active researchers are improving their own practices. However, as more lines of models continue to emerge and are changed by diverse research groups, new lines of inquiries will emerge. In particular, *which aspects* of a model are improved in later iterations either by the same research group or a different one? Are some aspects more likely to be improved when a model goes into deployment and gets used by policymakers? A hypothesis would be that follow-up studies applying a model to a specific context would need to use data specific to this context, which may contribute to better processes for calibration and validation. Research into variations of a model over time and across research groups has already occurred in other fields such as HIV research, where some models have been improved for about twenty years [80,95]. As the use of ABM in obesity research reaches a level of maturity, future assessments should use the latest iteration for each model and may start to examine changes across iterations.

Credit authorship contribution statement

Philippe J. Giabbanelli: Directed the study, Designed the methods, Wrote the manuscript. **Boone Tison:** Collected and analyzed the data. **James Keith:** Collected and analyzed the data.

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