Use of Agent-Based Modeling (ABM) in Psychological Research

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Abstract In this chapter, we introduce the general use of agent-based modeling (ABM) in social science studies and in particular in psychological research. Given that ABM is frequently used in many disciplines in social sciences, as the main research tool or in conjunction with other modeling approaches, it is rather surprising its infrequent use in psychology. There are many reasons for that infrequent use of ABM in psychology, some justified, but others stem from not knowing the potential benefits of applying ABM to psychological research. Thus, we begin by giving a brief overview of ABM and the stages one has to go through to develop and analyze such a model. Then, we present and discuss the general drawbacks of ABM and the ones specific to psychology. Through that discussion, the reader should be able to better assess whether those disadvantages are sufficiently strong for precluding the application of ABM to his/her research. Finally, we end up by stating the benefits of ABM and examining how those advantages may outweigh the potential drawbacks, thus making ABM a valuable tool to consider in psychological research.

Keywords Agent-based modeling (ABM) · Psychological phenomena · Cognitive dynamic

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1 A Brief Explanation of Agent-Based Modeling (ABM)

Agent-based modeling (ABM) is a computational analysis tool that simulates a system at various levels of detail and then uses the model to execute controlled experiments. Once the model is built, and similarly to empirical research, data is obtained from the model and analyzed through different statistical tools (ANOVA, regression equations, time-series analyses, and other methods better suited to analyzing nonlinear data) to draw conclusions about the system under investigation. The distinguishing feature of agent-based models (ABMs) is that they are constructed in a "bottom-up" manner, by defining the model in terms of entities and dynamics at a microlevel, that is, at the level of individual actors and their interactions with each other and with the environment (Canessa and Riolo 2006). An ABM consists of one or more types of agents (i.e., actors) and possibly a non-agent environment (see Fig. 1).

Agents are typically small computer code routines that encapsulate the behavior of individuals, i.e., the animate agents in terms of Fig. 1 (e.g., a model of legislators with some moral reasoning mechanisms used in deciding whether to approve or not a given law) or institutions (e.g., political parties), represented by the organization of agents in Fig. 1. Agents' central characteristic is that they are capable of executing autonomous actions, by performing the *if* ... *then* ... *else* ... rules in Fig. 1, but note that rules can be much more complex, e.g., including reinforcement learning (RL) and/or artificial neural networks (ANN). The environment is the landscape where agents reside and interact among them and with the environment, represented

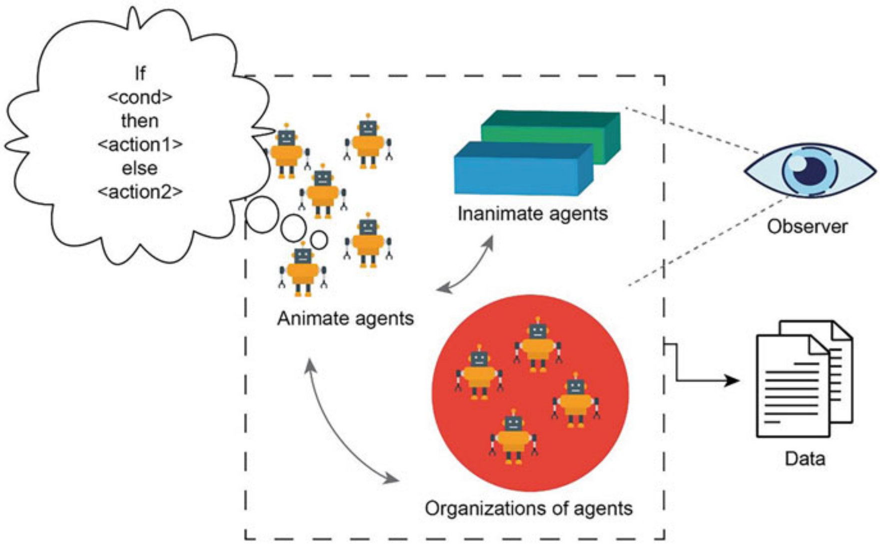

Fig. 1 Components of an agent-based model

by the dashed-line rectangle in Fig. 1 (e.g., the legislative rules, which legislators need to abide by when processing laws). Note that the environment could have internal states and also evolve by means of internal rules and/or by interacting with animate agents. Additionally, some ABM practitioners find it useful to differentiate between animate agents (already explained) and inanimate agents, which are static and do not have behavioral rules, i.e., they do not change their internal states along time. All these components of an ABM make up an artificial world, which can be seen by a meta-agent called the Observer in Fig. 1. The Observer has access to all the components of the artificial world, including the internal states of the agents and of the environment, which allows it to collect data from this world. These data will then be analyzed to study the dynamics of the ABM. This flexibility makes it possible to study systems at many scales and to integrate parts into a coherent whole. The state of an agent can represent various characteristics, preferences, beliefs, memory of recent events, as well as particular social connections. Agent definitions include specification of their capabilities to carry out particular behaviors, as well as decision-making rules and other mechanisms that agents use to choose their own behaviors. Agents also may have adaptive mechanisms (learning or evolutionary) that allow them to change based on their experience. As an ABM is run, agent behavior is generated as agents make choices that determine which other agents to interact with and what to do in a given interaction. Thus, ABMs embody complex interlaced feedback relationships, leading to nonlinear, path-dependent dynamics. Note that the model's output is both the temporal patterns in the micro-behavior of agents as well as the emergent macro-level structures, relationships, and dynamics that result from correlated microlevel activity.

Because we can do controlled experiments in ABMs, they can be used to enhance our understanding of processes that can lead to the patterns we see in the systems being modeled. For example, we can explore the role of various factors that vary across people in their decision processes by explicitly representing those factors in our models at the microlevel and then observing, at the aggregate group level, how the model responds to variations in those factors. We also can explore alternative microlevel mechanisms, for example, agent decision rules, as well as alternative social network structures. By systematically exploring a variety of simple ABMs, constructed from different combinations of components and mechanisms, we can test hypotheses about the underlying processes that generate the data patterns we see, including both hypotheses that are suggested by theoretical assumptions about human behavior and hypotheses generated by analysis of data from the field.

Finally, ABMs can make predictions that can be tested about what to expect in situations and times not yet studied, as well as predictions about what aggregate patterns to expect in variables not yet observed, thus suggesting additional questions to ask and cases to study. Because ABMs are dynamic, we can examine behavior of the system over various time scales and track the state of the system during the "transients" rather than just looking at equilibrium or other "snapshot" states of the system. Understanding the dynamics of a system is critical for gaining a deeper understanding of how the system being represented gets to the snapshots we obtain from empirical data. Because ABMs are computational models, they are formal, unambiguous, and thus replicable and testable (Axelrod 1997; Axelrod and Cohen 2000). However, they can be used to study aspects of systems that are difficult or impossible to study using traditional analytic (equation-based or game-theoretic) techniques (Parunak et al. 1998). All of these features of ABMs contribute to their suitability as a way to study the dynamical processes that characterize many psychological processes, both at the individual and the group levels.

In general, the development of an ABM consists of several stages, which are depicted in Fig. 2. For a more detailed treatment of this topic, a good paper to read is Macal and North (2010). First, and as with any model, we create an abstraction of the real system under study and write down an initial specification of the ABM. Then, we translate this specification into a computer code and make sure that the code reflects that specification, i.e., we verify that the code correctly implements the ABM. These two actions (codification and verification) are carried out until we are sure that there are no errors in the code. Now we have a verified ABM and proceed to validate it, i.e., make sure that the ABM represents the real system to a certain degree of detail/accuracy that allows us to use the ABM to study the real system. As Fig. 2 shows, validation is carried out by obtaining data from the ABM and from the real system and assess whether those data match to a desired degree. If that is the case, the ABM is validated. If not, we need to redo the specification of the ABM, by revising and accordingly changing the abstraction of the real system and performing again specification, codification, verification, and validation. After the ABM is validated, we execute controlled experiments, which allow us to get data from the ABM and analyze it to understand and/or explain the behavior of the real system, and perhaps predict it and make decisions regarding some relevant aspects of it. Regarding validation and doing controlled experiments with a model, note that

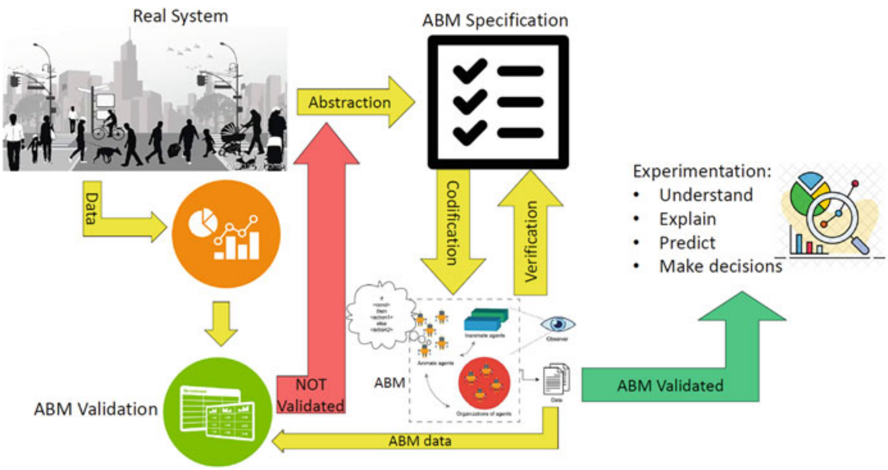

Fig. 2 Stages in the development and analysis of a real system using ABM

there might not be a strict equivalent in psychological research. We will discuss those issues further along in the current chapter.

After the reader has gained a general vision of ABM, we next discuss the reasons why ABM is seldom used in psychological research.

2 Why Are ABMs so Seldom Used in Psychological Research?

Though ABM is widely used in conjunction with other analysis tools in many fields, its use in psychological research is much less frequent. To illustrate, here we give just a small glimpse of ABM's applications in different fields: in social sciences, economy (e.g., Tesfatsion 2002), anthropology (e.g., Kohler et al. 2005), business administration (e.g., North and Macal 2007), and sociology (e.g., Macy and Willer 2002); in life sciences, biology (e.g., Alber et al. 2003) and ecology (Mock and Testa 2007); and in engineering, traffic routing (e.g., Bazzan and Klügl 2014), optimization (e.g., Fikar et al. 2018), and socio-technical system design (e.g., Shah and Pritchett 2005). We believe that there are different reasons why ABMs have had little impact in psychology. In the next paragraphs, we explain those reasons, starting with the more general ones.

2.1 General Reasons of the Infrequent Use of ABM

Codification of the ABM: Like any computational model, an ABM is a computer program that needs to be specified at a macro- (e.g., how agents might aggregate in different groups or organizations) and microlevel (e.g., particular behaviors of the agents) and then coded in a certain programming language. As such, we need to express agents' behavior in detailed rules that must be translated into computer code. Hence, our model needs to be based on theory that can at least potentially be expressed in mathematical functions and/or logical rules. This may be a first hurdle in building an ABM if we do not know enough of the internal details of how the system works, which is typical for mental processes studied in psychology.

Verification of the ABM: Before any analysis is carried out with an ABM's output, we need to make sure that its specification is correctly translated into computer code. Fortunately, there exist useful software developing and testing practices that allow decreasing the probability of making errors when coding the ABM and afterward also checking that the code is free of errors and that it conforms to the model's specification (e.g., Pressman 2010). Given that many mental processes are very complex, representing them through rules, and then translating those rules to code, may require a detailed knowledge of those processes. However, in psychology, we frequently do not know sufficient details of the relevant processes. This may preclude us from making a strict one to one mapping from general practices in ABM modeling in other fields to its use in psychology. We will discuss this topic in greater detail in the coming pages.

Validation of the ABM: While ABM and all formal models, in and of themselves, increase our knowledge about the behavior of any system consisting of similar processes, to use such models to make inferences about particular real-world systems requires model validation. Validation is the process by which we make sure that the ABM represents the real-world system closely enough, so that it enables us to answer our research questions, and thus, we can confidently draw conclusions that are scientifically informative. However, model validation for ABM is not trivial (Grimm et al. 2005; Grimm and Railsback 2005). ABMs generally have many input parameters, and thus the parameter space tends to be huge. Because interactions generally exist among parameters, validation requires simultaneously varying many parameters, which amounts to trying millions of possible combinations. Given that ABMs may effortlessly grow in size and number of parameters compared with other types of models, e.g., mathematical, this makes ABMs harder to validate. In general, it exists a relative consensus among ABM practitioners that a good procedure is to apply the *KISS* (Keep It Simple Stupid, Axelrod 1997) principle. This means that we should start with an as simple as possible model and then add details only if necessary (i.e., normally include more details only when the ABM does not reach validity). Finally, another possibility to ABM validation is to reach relational equivalence, i.e., matching patterns and relationships between the model and the system being modeled, rather than trying to match details (Axelrod 1997). That is, we assess whether the general behavior of the model matches that of the real system. For example, if the model shows that as we increase the value of a parameter, we observe an increase in an output variable of the model, then a similar change in the corresponding "parameter" in the real system should result in a similar change in a corresponding measured variable of the real system (Canessa and Riolo 2006).

Reaching a useful trade-off between ABM's detail and validation: On the one hand, if we try to incorporate into an ABM a very detailed representation of the real-world system, this makes codification, verification, and validation extremely difficult. Contrarily, if we simplify the ABM too much, its codification and verification will be easier, but we may not achieve a sufficiently valid model. Thus, it is still an open issue how to proceed. In general, and as already mentioned, a good procedure is to apply the *KISS* principle, starting with a simple ABM and then incrementally add details only if necessary. However, this practice may also lead us to a *tinkering* pitfall (Murphy 2005). This problem arises when a researcher develops an ABM that in general successfully models a system (e.g., accounts for most of empirical data) but does not explain some other part of the same data or different data. Thus, the researcher incrementally modifies the ABM to better account for a larger portion of the data. However, in doing so, the researcher ends up with a model that naively puts together different processes (hopefully of the real-world system) without any theoretical consistency/coherence among them. This is similar to overfitting a regression model, where we can add more explanatory variables to the regression and almost always obtain an increment in explained variance, but loosing parsimony, generalization, and explanatory power.

Replicability of ABM's results in the real system: Closely related to validation issues, an ABM's results, though interesting and thought provoking, may not go beyond mere "thought experiments" (Axelrod 1997). Once an ABM is developed and verified, we may effortlessly begin doing many experiments, which is even an advantage of ABM. However, to draw sound conclusions from those experiments, we need to replicate them in the real system. Here, one may claim that after an ABM is validated, conclusions from ABM experimentation should also be valid. Nevertheless, as with all models, validity is always restricted to some subset of the parameter space (i.e., to some ranges of the values of the model's parameters) or to the context of the study. For example, in a decision-making study, if subjects must decide under time pressure (context of the study), the type of processing that could operate could be mainly associative. On the other hand, if the study does not involve decision-making under time pressure (a different context), a deliberative model might be more appropriate. The same happens with ABMs. Though we may establish an ABM's validity, this does not guarantee that we can always draw sound conclusions outside a close-enough range of parameter values within which we validated the ABM or, similarly, if we change the context of the phenomenon for which the ABM was developed. This is not to say that ABM's conclusions are not useful but that we always need to carefully ponder the use of ABM's results and, if doubts exist, try to replicate results in the real system. However, for several reasons, doing that might be difficult. Some examples of that are when there exist economical and/or ethical restrictions that prevents doing that (e.g., economical, test a vaccine against a disease in a whole continent in a short time period; ethical, letting a virus disease spread to see how many people die), or when it is impractical to do that (e.g., confine whole countries for years to see whether we can control the spread of a virus disease), or because it is very difficult to do some controlled experiments in reality (e.g., test whether people's specific patterns of movements in the real world correlate with the spread of a virus disease).

2.2 *Specific Psychological Research-Related Reasons of the Infrequent Use of ABM*

Additionally, to the above-discussed general reasons for why ABM is sometimes difficult to use in research, we believe that there are some other issues specific to psychology that hinder its utilization in the field.

There might not be strict equivalents to model verification and validation in psychological research: Throughout this chapter, we have hinted at general difficulties that may arise when trying to use ABMs to model psychological phenomena. Some of these difficulties relate to the issues of verification and validation. As we have discussed above, verifying and validating an ABM require access to the real-world system to a sufficient level of detail. In contrast, psychological models are typically highly theoretical, such that many of their mechanisms are not directly measurable and remain hidden from the researcher (for practical reasons or even in principle). To illustrate, imagine a theory about logical reasoning that tries to explain how people draw conclusions from premises. Here, the experimenter would manipulate premises and measure conclusions, and the model (i.e., theory) offers a mechanism that might account for the observed regularities linking premises and conclusions. Contrary to a mostly transparent system that could be of interest in, e.g., engineering, systems under study in psychology typically remain opaque. Thus, the goal of using an ABM that is sufficiently close to the real system it models to carry out experiments that are not possible to carry out given practical or ethical considerations is a hard to achieve goal in psychological research. In consequence, we might argue that when ABMs are used in psychology, model fitting is what researchers can in practice do.

Difficulty in fitting ABM's outputs to data: In psychological research, and especially when developing computational models, there is an emphasis in using as a model's measure of success how well it fits the corresponding empirical data, i.e., model fitting. This is normally done by adjusting the free parameters of the model, so that its relevant outputs match as close as possible the empirical data. Models that are not amenable to such procedure may still be able to make qualitative predictions (e.g., predicting differences in means across experimental conditions) but are definitely less appealing. We already discussed validation and saw the difficulties in reaching them for ABMs. Hence, those difficulties can impact the extent to which model fitting can be done for ABMs and hinder a more straightforward application and acceptance of ABM in psychology.

Difficulties in using model fitting as the main ABM's success measure: There are some differences between validation, as described above, and model fitting as is generally done in psychology. In computational models in psychology, it is generally possible to describe model complexity by keeping track of the number of free parameters the model allows (i.e., more free parameters, more complexity). This means that models can be formally compared based on their number of free parameters (e.g., the Akaike Information Criterion, AIC, Akaike 1974). However, the number of free parameters is not necessarily a good proxy for an ABM's complexity. The researcher has many other decisions that increase the model's degrees of freedom and will not necessarily reflect in a model's free parameters. In ABMs, the model may involve many decisions about the simulated system's structure that are not strictly speaking considered parameters (e.g., agent's decision rules, environment structure). This is perhaps why the *KISS* principle (Axelrod 1997) is a mostly qualitative judgment regarding model complexity and is not strictly equivalent to the typical numerical model evaluation formulae available for computational models used in psychology (e.g., the AIC). This problem, together with the typical relative lack of access to the real-world system that wants to be modeled, makes evaluating an ABM's fit to data difficult to judge. Relatedly, the ideal of using an ABM to conduct controlled experiments with a validated model is generally difficult to achieve in psychological research, precisely because of the lack of access to the real-world system.

Perception that ABMs are less formal than other types of models: In psychology, there is a long tradition of modeling mental processes using mathematical models (e.g., see Murphy 2005) and also a more recent trend of using computational models, for example, based on neural networks (e.g., Murphy 2005). Although there is still controversy regarding the latter ones, when sensibly applied to psychological research, these computer-based models have helped to advance the knowledge of the field (Murphy 2005). However, ABMs are still perceived by many researchers as lacking the formality of mathematical models and even of computer-based models. Mathematical models tend to be tractable, unambiguous, and generally can be solved in closed form. Also, they are elegant and their internal consistency and external coherence with other models may be checked without too much effort. On the contrary, ABMs are harder to develop, verify, and especially validate and do not provide closed form solutions. Those ABM's characteristics create a perception that ABMs are not as formal as other types of models. However, we would like to argue that being a model makes ABMs similar to mathematical models and for some situations even better than mathematical models. In ABMs, the constituents of the model need not be homogeneous as generally assumed in mathematical models in order to solve them in closed form. Moreover, in ABM, we can represent systems with different feedback loops, local information processing parts, and adaptive mechanisms, leading to the nonlinear behavior of the system. This makes ABMs especially suited to analyzing and tracing the dynamics of the system's outputs, so as to learn how the system evolves in time. Finally, ABMs may be able to more simply express in computer code complex behaviors and interaction rules, freeing the researcher to better convey his/her theory in the model. Here, we must note that any model is an abstraction of reality, and thus the modeler needs to always leave out of it some aspects of reality. ABMs allows a researcher to more easily do that in incremental steps, pondering the consequences of his/her modeling choices and, if needed, include in the model mechanisms of the real system that would otherwise be difficult to express in mathematical form.

Restricted vision of what an agent is: It is intuitive to see a computational agent as a representation of an individual. In this view, an agent is an individual capable of executing autonomous actions based on some internal mental processes, i.e., based on some behavioral rules. Additionally, agents interact among them and with the environment based on those rules. Much of the use of the term agent in social sciences, and economy in particular, reinforces such preconceptions. Given that in psychology the focus is on studying the "internal processes" of an individual, that restricted view of an agent, which emphasizes the interaction among agents (i.e., individuals), does not match the psychological mainstream research. However, an agent may be much more general than just representing individuals. For example, an agent may be an institution or some other form of social group (e.g., schools and families, Canals et al. 2022). Additionally, even if agents represent individuals, there are psychological research to which that paradigm is applicable. For example, in our own work, we have applied ABM to study the listing process in a Property Listing Task (PLT), where agents list properties for a concept (Canessa et al. 2018; cf. Canessa et al. 2021). In that ABM, agents have a mental retrieval process based on Atkinson and Shiffrin (1968) human memory and recall process (more recently revised in Malmberg et al. 2019), and we have been able to model the listing process dynamics for concrete vs. abstract concepts, obtaining relational equivalence in the listing process dynamics for such types of concepts (cf. Canessa et al. 2021). In another ABM, we have modeled the dynamics of the salience of stereotypes and negative stereotypes among groups of people that have power asymmetries between those groups (Lagos et al. 2019). That ABM allowed us to explore that phenomenon and preliminarily explain why negative stereotypes, although detrimental to the group that keeps them, are nevertheless preserved by that group. Finally, note that agents may also represent the mental components of an individual, e.g., the different executive processes of the retrieval process and its interaction with long-term memory, working memory, and so on. Hence, agents are not necessarily restricted to characterizing only individuals and the interactions among them.

3 Use of ABM in Psychological Research and Its Advantages

Having discussed the principal difficulties of applying ABM to psychological research, we end this chapter by considering why ABM is still a valuable and viable tool for the field. We concede that as part of our previous discussion, we have already presented some of the advantages of using ABM. However, we believe that a more explicit treatment of this matter will allow the reader to more sensibly decide whether his/her research may benefit from using ABM. We think that the reasons to use ABM and the related advantages may be divided into more conceptual and more practical/pragmatic ones. Thus, we begin presenting the conceptual reasons and then the practical ones.

3.1 Conceptual Benefits of Using ABM

Analytical vs. *synthetic approach*: In general, in science, researchers normally use the "divide and conquer strategy," i.e., given that a system under study may be huge and encompass many complex processes, we simply divide it into pieces and study those parts in relative isolation from each other. After we have obtained a reasonably good understanding of the parts, we try to connect those parts in a hopefully coherent whole model to analyze the real system. However, this approach assumes that those parts of the system do not strongly interact among them, so that they can be studied relatively independently from each other. In many systems, that is generally not the case (Bankes 2002), and thus we need to explicitly analyze the interactions among the various components of the system. Hence, in an ABM approach, which we label *synthetic*, because we synthetize (i.e., build) the artificial world (system), it is possible to explicitly include and study those interactions.

Equilibrium vs. *Nonequilibrium supposition*: That social systems always get to an equilibrium state is a typical supposition in social sciences (e.g., in economy, markets get to equilibrium between the offer and demand of goods by adjusting the price of goods). Unfortunately, in many systems, the evolution and coadaptation of the system's entities lead to positive feedback loops, undermining such assumption. Under such situation, systems exhibit statistical macro regularities, although they show disorder at the microlevel. The abovementioned example of economic markets is an instance of that. Although we may see that markets somewhat regulate prices at the macro level (i.e., at the level of aggregate institutions), the behavior of prices at the microlevel (i.e., individuals) is far from equilibrium. Thus, to better understand and explain economic behavior and dynamics, we need to study nonequilibrium dynamics of the system, which is more easily accomplished by using ABM.

Nomothetic vs. *generative method*: In the nomothetic method of science, a researcher experiments with the real system, hopefully doing controlled experiments, obtains data and analyzes those data to study the system. But, what can we do if we cannot experiment with the system, as we already saw? Using ABM, we can explain the system's regularities by deriving the mechanisms that generate those regularities, generally at the microlevel. Axelrod labels this a *generative* approach (given that it generates the artificial system) and regards it as the "Third way of doing science" (Axelrod 1997). In the same vein, as Epstein says "If you haven't created it, you haven't explained it" (Epstein 1999). Of course, no practitioner of ABM claims that this generative method is always easy to do, but at least, it is another possibility to explore.

Models based on variables vs. *configurative ontology*: Generally, most models and especially mathematical models are based on variables and equations that relate those variables to each other. Nevertheless, using variables and equations, it is sometimes very difficult to capture the complex behavior of social systems. Moreover, generally equations assume homogeneity of the different parts of the system, so that those parts can be represented by variables. Given that a system may have a configuration of interactions among actors and aggregate level structures, a sensible model of the system needs to account for those characteristics. With ABM, it is relatively easy to endogenize those actors and interactions, leading to a more sensible representation of reality.

3.2 Practical Benefits of Using ABM

We hope that by now, the reader may have appreciated some of the advantages of considering using ABM in his/her research. Now we complement them with the next more practical/pragmatic advantages of applying ABM.

Use a simulated system when it is impossible to study the real system: Oftentimes, we cannot experiment with the real system because of ethical, economical, and/or practical issues. Thus, with an ABM, we can at least open a window to the system and perform controlled experiments. Of course, that assumes that the ABM was verified and validated. Regarding validation, which might be the most difficult part of the process, remember that validation may be done at various levels of detail. Here, achieving relational equivalence might be a good and valuable alternative. However, we recognize that in psychology, mainstream research uses model fitting to assess validity, i.e., the model is valid as long as it replicates empirical data to a certain degree of accuracy. Thus, given that relational equivalence only replicates patterns in data, not the exact data points, some researchers might regard relational equivalence as not a formal enough method for assessing validity. However, even if model fitting is not completely possible, the ABM may be used to gain insights about the real system and do "thought experiments." These "thought experiments" may be especially valuable when they lead to find counterintuitive results that may be considered critical predictions of the model.

Attrition of sample in longitudinal studies: In social sciences, longitudinal studies are based on small sample sizes and a few measurements of variables over time (Quezada and Canessa 2010). Additionally, since in many studies the analysis relies on the specific context of the situation, it is difficult to generalize the findings. Those problems are also reinforced by the attrition of the sample along the time span of the study. With ABM, we can get as much data as needed, which allows a very precise characterization of the dynamics of the system (Quezada and Canessa 2010). And we already explained why the analysis of real-world systems needs to include the dynamics of such systems: because of nonequilibrium and to assess how the system gets to the states/equilibria we are observing.

Documentation and formalization of the model: Given that we must translate the specification of the ABM to computer code, all of the processes, behavioral rules, and components of the model must be precisely defined, without any doubt regarding how the description of the various parts is implemented. That formalizes the model and helps assess whether we must think in greater detail the verbal specification of the model. Anything that is not amenable to be coded must be specified with greater detail. Moreover, the computer code provides for a deeper documentation of the model, and thus, the ABM's details are more transparent to researchers. This allows a better and more in-depth scrutiny and critique of the model.

Explain and understand the model in a research group: Most research is conducted by groups of scholars and always the mutual understanding, and discussion of the model among group members is a concern. How can we make sure that all the group members share the same understanding of the model, especially if the model is rather huge and/or complex? Given that the ABM is finally implemented in computer code, that code is an unambiguous and detailed description of it. That allows exposing the different views about the model and better get an informed consensus about the model. Additionally, if someone disagrees with some parts of the model, it is relatively easy to change the corresponding computer code and see the consequences of those changes on the outputs of the model and corresponding conclusions. Closely related to that aspect is that we can perform sensitivity analysis of the various parts of the ABM. If we change some parts of the ABM and the outputs do not vary too much, or if that variation does not alter the conclusions, then we can say that those parts are not so important and the model is robust to those variations and that the conclusions are more generalizable.

Effectively and efficiently communicate analyses and results: Closely related to the preceding point is that an ABM allows for a more effective and efficient communication of analyses and results to the research community. First, results are easily conveyed to an audience given that ABM's development platforms have nice graphic user interfaces (GUI), which allow building many different views of the artificial world and plots of many ABM's outputs of interest. That helps visualize the behavior of agents and the dynamics of the outputs in real time. Moreover, all of that can be done at various levels of analysis at the same time. Second, if someone wants to do "what if" type of analysis, that can be done by simply changing the settings of the corresponding parameters of the ABM (by moving the respective sliders of the GUI) and immediately observing the impact of those changes on the relevant outputs of the model. Third, if someone questions parts of the ABM, and the associated computer code is rather easy to modify to accommodate that critique, we can immediately deal with those concerns, assessing whether the criticism is really warranted or not. A substantial change in ABM's output and/or conclusions will tell us that the observation is worth further consideration.

Finally, we would like to say that this chapter does not intend to oversell ABM as the sole cure for all the problems empirical and other types of research exhibit but honestly present the benefits and disadvantages of ABM. By having those antecedents, the reader must ponder them and assess whether the advantages outweigh the drawbacks for the research he/she wants to conduct. Our own experience and work with ABM show that indeed ABM is worth considering in psychological research.

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