Theory building via agent-based modeling in public administration research: vindications and limitations

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Abstract

Purpose – The purpose of this article is to provide an overview of agent-based modeling as an alternative method for public administration research. It is focused on encouraging public administration scholars to come to better understanding of the method.

Design/methodology/approach – This article performed a comprehensive review of methodological issues relative to agent-based modeling.

Findings – After reviewing the current research themes in public administration and the methodological nature of agent-based modeling, we found that agent-based modeling can help researchers to advance theories by means of sophisticated thought experiment which is not possible by formal modeling and verbal reasoning. We also pointed out that agent-based modeling does not substitute empirical research, but can add much value through being part of a mixed-method and multidisciplinary research.

Practical implications – We suggested that interested researchers may need to take a strategic approach in developing and describing a pertinent model and reporting its results.

Originality/value – Agent-based modeling has rarely been used in public administration research. The article provides an introductory overview for researchers not familiar with ABM and suggests to the academic community future venues that would unfold from agent-based modeling.

Keywords Agent-based modeling, Experiment, Simulation, Complexity, Theory building, Computational

Paper type Conceptual paper

Introduction

Computational modeling has been largely used in various fields of general social sciences (Axelrod, 1997; Cederman, 2005; Epstein, 1999). However, there has been relative paucity of methodological attention to the computational modeling approach in the public administration literature. In this article, we provide an overview of computational modeling, specifically agent-based modeling (ABM), as an alternative method for public administration research. We especially put emphasis on the potential of ABM to become conducive to theory development.

Recently social science scholars have been accustomed to the idea of complexity as a lens through which to understand social issues. In the realm of social sciences, assumptions on human beings have often intended to treat complex human cognitive processes, behaviors and interactions as simple (Harrison *et al.*, 2007, p. 1230). For example, perfect rationality with perfect information and self-interested motivation of people stemming from classical economics has dominated decision-making studies, even in such cases as

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marriage, donation and prosocial behavior that apparently do not fit well with the assumptions (Bowls and Gintis, 2011; Thaler and Gasser, 2015). More and more scholars have realized that the rationality assumption may serve well for formal reasoning, but not well for explaining the complexity of social phenomena and ostensibly not rational human behaviors.

Public administration literature has specifically paid attention to interdependency and interaction among people and social problems. Research on networks has increased as social service provision (Milward and Provan, 2000), collaborative governance (Ansell and Gash, 2008; Emerson *et al.*, 2012) and disaster management (Wise, 2002, 2006) have gained attention since the 1990s and 2000s. Witnessing public policy failures against wicked social problems (Head, 2008), scholars began to think about the nonlinear and complex nature of social problems (Weber and Khademian, 2008). The ensuing viewpoints point to the research objects prevalent in these days not suitable for a linear modeling; instead, they point to the imperative to understand the underlying complex mechanisms, through which those phenomena emerge. The traditional linear modeling has yielded rigorous analytic methods to depict rather simple and straightforward relationships among variables; but has troubled scholars struggling with complex social phenomena and seeking better modeling methods to deal with those phenomena. Computational modeling, particularly ABM, has features rooted in unique ontology and epistemology advancing search for relationships between agency and structure and explaining complex social phenomena [1].

The ontological root of ABM stems from the systems science and the cognitive science, addressing concepts such as "cellular automata" and more sophisticated "complex adaptive systems" and "distributed artificial intelligence" (Holland, 1995; Smith and Conrey, 2007; Weiss, 1999). These concepts refer to an individual agent or a group of artificial agents that perform a certain set of tasks under a given condition, usually in the absence of a central coordinating mechanism. Early works such as the garbage can model (Cohen *et al.*, 1972), and Schelling's spatial segregation model (1971) have shown the veiled potentials of ABM. However, according to Harrison *et al.* (2007, p. 1231), "during the 1970s and 1980s, computer simulation "settled into a tiny niche, mostly on the periphery of mainline social and organizational science" (March, 2001, p. xi)."

Nevertheless, ABM has crept over the time into the field of public administration research and gained attention in the 2010s. Some pioneering works have focused on agent interactions in collaborative governance and were published in public administration journals such as *Journal of Public Administration Research and Theory* (Johnston *et al.*, 2011; Choi and Robertson, 2014b), *Public Management Review* (Robertson and Choi, 2012) and *International Public Management Journal* (Choi and Robertson, 2014a) during the first half of the 2010s. It is now worth reviewing the potentials of ABM conducive to study of public administration.

In this article, we first undertake an overview of ABM, explaining its definition, epistemological ground and key research themes and questions that public administration researchers can cope with by resorting to ABM. ABM has been aligned with theory development, stimulating concept refinement and model devising and integration of different theories, drawing on its strength to buttress computer-aided thought experiment to generate deductive propositions/hypotheses. In the second part of this article, we attempt a critical review of the features germane to ABM, followed by account of its limitations. We bring particular attention to the nature of knowledge ABM generates that may not be replaceable of, but be compatible with empirical findings. We also touch the issue on topic selection. Limitations of ABM will be followed by ways to mitigate the drawbacks. The remedial formula will include resort to a mixed-method approach and to multidisciplinary research. Finally, we suggest pedagogical implications of ABM for those interested in utilizing the method.

Overview of ABM

In this section, before we review the potentials of ABM for contributing to public administration research, we give an overview of ABM, beginning with its definition, epistemological ground, basic building blocks and internal mechanism.

Definition of ABM

Smith and Conrey (2007, p. 87) defined ABM as "simulation of large numbers of autonomous agents that interact with each other and with a simulated environment and the observation of emergent patterns from their interactions." In the same vein, ABM is defined as "a research method used to model how system-level characteristics emerge from complex local interactions among agents" (Choi and Robertson, 2014b, p. 501). Harrison *et al.* (2007, p. 1234) took the similar approach by defining ABM as "a computational model of system behavior coupled with an experimental design." In these definitions, it is clear that ABM has been in use to model/simulate an emergent phenomenon by linking local agent interactions with structural characteristics, while between them lying complex internal mechanisms realized by the method. These definitions deserve careful attention, as they point to both the potentials and limitations of ABM, which we will discuss in the following section.

The prevalent definition of ABM has weight on its methodological nature, even though it needs to be emphasized that ABM is a modeling method bent on finding the best path to theory building. The latter attribute links the emergent phenomenon from local interactions of agents with the micro- and macro-level analysis (Choi and Robertson, 2014b; Smith and Conrey, 2007).

Epistemological ground

As implied in the definition, ABM is based on a distinct epistemological ground on social phenomena. Contrary to the emphasis on its methodological dimension often observed in the subfields of social sciences, founders of ABM took a rather strong stand in connecting the relevant epistemology with the exhibited features of social phenomena. As Epstein (1999, p. 41) put it:

> [T]he agent-based approach invites the interpretation of society as a distributed computational device, and in turn the interpretation of social dynamics as a type of computation.

As such, we summarize the epistemological ground of ABM in two ways: "generative or emergent" and "computational."

Generative/emergent. ABM is a methodological tool equated closely with what Epstein (1999) called "generative social science" (Cederman, 2005), although "emergent" is a more popularly used word today. By generative, Epstein (1999, p. 44) meant that ABM is not inductive but deductive in that the method generates computational results-a macro-level structure built up on a given set of assumptions of agents, rules and environments. In the similar epistemological vein, Smith and Conrey (2007, p. 88) emphasized the bridging role of ABM "between the micro level of assumptions regarding individual agent behaviors, interagent interactions, and so forth and the macro level of the overall patterns that result in the agent population."

Schelling's classical model of spatial segregation (1971) is a good example to demonstrate the nuts and bolts of ABM. The model generates a map of spatial segregation exhibited between two groups of agents. It happens by simply using a threshold rule that agents move to another place on the map when they want *some* of the neighbors to be proximate to the same group. An actual simulation shows a surprising degree of spatial segregation generated from the simple rule, even when the threshold is low.

There have been impressive arguments endorsing theoretical status of ABM with its methodological competency. Scholars using ABM contend that the model comes out of theoretical review and the model is itself an apparatus of theoretical conception. Some even go further to argue that the model *is* itself a theory (Carley and Gasser, 1999; Cohen and Cyert, 1965; Harrison *et al.*, 2007; Sun, 2009). A specific agent-based model connotes that an emergent social phenomenon such as spatial segregation (Schelling, 1971) can be sufficiently generated by a couple of simple rules that agents follow. Consequently, as argued by Epstein (1999, p. 42), computational demonstration of macrostructure is *taken as a necessary condition for explanation itself*. The connotation stimulates us to say that ABM corresponds to a structure of a theory, as well as of a methodology.

Computational. The generative power of ABM is supported by its computational attributes. According to Carley (2002, p. 7257), who contributed to development of ABM and social simulation in general, a computational organization science is a "a neo-information-processing approach … that combines social science, computer science, and network analysis." This approach supports perceiving groups, organizations or social systems as distributed intelligent systems composed of multiple agents (Weiss, 1999), and their interactions as ancillary patterns of information sharing and learning.

The computational nature of ABM has two pronounced merits. First, simulation results can differ depending on parameter values. Staying this way, ABM can be not simply a different logical reasoning avenue to get to formal deduction, but a good operational tool useful for addressing the stochastic nature of social issues. For example, simulations by the Schelling model yield different shapes of spatial segregation; all the results are a deduction from the initial condition and rule. However, the computational nature of the model renders the simulation results to be more explicit variants or nuanced versions of formal deduction. Second, ABM can demonstrate "surprising" conclusions from the initial assumptions. Spatial segregation may occur in the Schelling model even when agents want to see only one-third of their neighbors proximate to the same group (Schelling, 1971). As such, not all logical consequences of agents' local interactions can be expected from the verbal reasoning that follows the previously set assumptions about the agents. In this way ABM can be coupled with sophisticated computational designs and exhibit a wide range of computational consequences out of theoretical assumptions (Choi and Robertson, 2014b).

Building blocks of ABM

In this section, we describe the conceptual building blocks comprising ABM, beginning with the basic blocks including agents, rules and environments (Epstein and Axtell, 1996). Since this article proposes to describe how ABM can be used to excite and animate knowledge environment in public administration, particularly in theory development, we narrow down our discussion to the theoretical aspect of the building blocks [2]. Figure 1 illustrates the basic building blocks of ABM.

Agent. A researcher may first define an agent as the basic element of the model. Since ABM "grows" a group, organization or society through multiple agents' interactions, the definition of key agents is the starting point for maneuvering ABM. An agent is not necessarily a human being equipped with cognitive agency; it can be whatever entity capable of processing information, making decisions and taking actions (e.g. an organization can also be an agent). What is important is not the unit of an agent, but the researcher's theoretical concern-to proceed from what level to grow the society.

An agent possesses two elements: properties and functions (Figure 1). The former includes characteristics of agents such as goals, information, resources and demographics. In the Schelling model, for instance, an agent can be defined as an entity possessing properties such as social preference (in the original model) and income, if necessary. The latter defines the

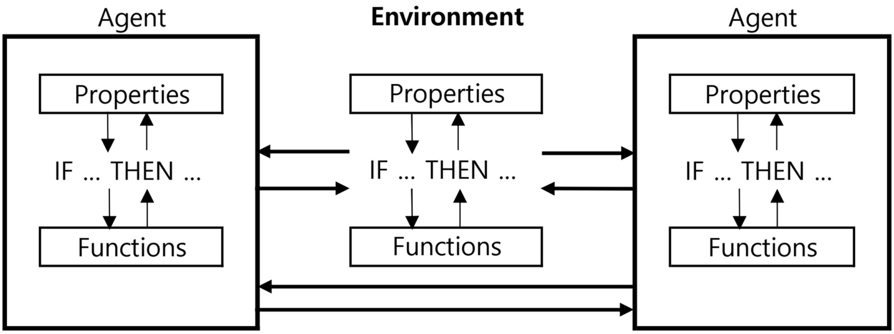

Figure 1.
Building blocks of ABM

agent's behaviors such as exploring, sharing, updating information and handling resources. In the Schelling model, agents "recognize" part of their neighbors, and "move." Similarly, one can simulate group polarization during a deliberation process. In this case, the agent is individual group members who possess initial preferences and information, and contact with other members and change preferences. In practice, agents are often designed as *boundedly rational*, and in such a way to adapt to the outside conditions through *learning* from *local interactions*. In actual models, agents usually move (Epstein and Axtell, 1996; Schelling, 1971), search (Maroulis and Wilensky, 2015), vote (Choi and Robertson, 2014b) and make coalitions (Scott *et al.*, 2019), while updating their properties and functions according to feedback (arrows in Figure 1). The concept of "complex adaptive systems" or *CAS* (Holland, 1995) has often been used to represent the adaptive capabilities of agents.

Rules. The second building block is rules. Rules are typically signified by "IF. . . THEN. . ." as denoted by interacting arrows in Figure 1. Rules, first of all, include the actions of agents. For example, an agent would obtain information from another agent based on their homophily; in this case, the agent's decision is affected by its preference, but the action is based strictly on the abstract rule that reflects the preference: "agree if and only if the information is compatible with your preference." Second, rules include norms and institutions beyond the reach of an agent. For example, although each agent may act to vote for or against an agenda, there can be a group level decision rule – unanimity or majority (Choi and Robertson, 2014b). That being said, rules in ABM are usually embedded in agents or the environment in the form of function of interactions.

More recently, scholars have been at work to combine the concept of Institutional Grammar with ABM (Siddiki *et al.*, 2019, p. 19). In this case, the decisional rules posit institutional statements as "shared linguistic constraint or opportunity that prescribes, permits, or advises actions or outcomes for actors" (Crawford and Ostrom, 1995, p. 583). In the same vein, the rules are "categorized and dissected in accordance with the appropriate linguistic syntax" (Siddiki *et al.*, 2019, p. 5). These are illustrative of the pronounced attempt to magnify the central role assumed by rules in theory building.

How a researcher defines rules should be determined by relevant theoretical propositions or hypotheses, whether empirical or logical. In the case above, a preference based on homophily and resulting behavior can be designed according to what has been found in group research (De Drew *et al.*, 2008). Then, why a certain macro-level structure has emerged becomes a query to be explained by referring to those rules. Therefore, it would be asserted that relevant theoretical assumptions can and should be included in a model as rules.

Environment. The third building block of an agent-based model is environment. A design of environment is related to "controlled" macro-level variables or conditions in which agents play. Schelling's (1971) spatial segregation model employed a two-dimensional grid space as environment. Some study in the organizational population ecology designed more abstract environment to cater to its theoretical concern: density, fertility and turbulence (Epstein and Axtell, 1996; Mezias and Lant, 1994). Collaborative governance research, by contrast, often does not require physical environment.

Whatever the nature of an environment may be to the agents in the real world, environment can be designed as an omniscient agent as shown in Figure 1. A properly designed environment is capable of accommodating basic level agents, of asking tasks and demands, and of giving feedback after evaluating agents' performance. At a casual glance, an agent may not grasp the whole feature of the environment; but only interact with it locally as much as it is known to the agent.

Internal mechanism. Other than the three basic building blocks of ABM, it is worth considering the role of the internal mechanism built in a specific model as an auxiliary building block. The auxiliary building block affects how the model works to generate the resulting structure. As a methodological merit, ABM can grow apparently complex phenomenon out of a few simple rules and agents. So, in between the ensuing structure and basic building blocks lies the internal mechanism of the model. The internal mechanism specifies the way through which multiple agents, rules and environments generate simulation results. If various rules are designed for agents to interact heavily with each other, the internal mechanism of the model becomes more intractable. Intractability is apparent when the designer may not explain verbally why a certain simulation result came out the way it did [3]. The internal mechanism has varying levels of tractability amenable to control by modelers. Out of this, one may say that a model is more transparent when it is more tractable.

There is a trade-off between the generative power and the tractability of a model. By adding more agent properties and rules, the Schelling model, for instance, could generate more real and diverse results; however, it becomes more difficult to sort out the effect of each property or rule. After all, it may be noted that although a researcher may not directly control the internal mechanism of the model, he or she can design the model in such a way to take control of the level of the tractability. Typically it is by using a stepwise or experimental design through which results are compared.

Potentials of ABM for theory building

How ABM helps

Computer-aided simulation in general is often used to simulate the real world as closely as possible, as the flight or military training simulators do. The permeation of ABM in social sciences, however, makes scholars inclined more toward thought experiment than real-world simulation. From this standpoint, we move on to suggest potentials of ABM for theory building.

First, ABM can serve for expanded formal modeling to address complex conditions. If a model begins with relatively simple and homogenous agents and rules, formal modeling would better serve to the end of transparency, comparability and tractability (Harrison *et al.*, 2007; Kreps, 1990; Miller and Page, 2007). When agents are defined as possessing different preferences and functions with several rules to interact with each other on, ABM would better serve to the end of heterogeneity and complexity, as might be seen in an *n*-person game with multiple rules and long iterations.

Second, theory refinement and integration can be facilitated by ABM. By encouraging scholars to operationalize key concepts fed into agent designs and rules, ABM can refine and integrate different theories into a streamlined whole. Social scientific concepts are not always clear enough for use in a computational model. For example, when a researcher designs a scheme for human collaboration or an incentive system, it is critical to designate the subject to be prosocial or proself (Bowls and Gintis, 2011; De Drew *et al.*, 2008). Researchers are then required to algorithmically define being prosocial or proself (Axelrod, 1997). Next, developing a model necessitates review and piling of specific theoretical propositions to stipulate actors and interaction mechanisms. It is also necessary to define concepts like homophily, preference and collaboration and translate them into rules. The work usually involves literature review and familiarity with various approaches in the pertinent field. Above all, designing a model requires a careful weaving of theoretical elements to assure consistency with each other in the model. Harrison *et al.* (2007, p. 1233) pointed out that this process "imposes a discipline on theorizing, forcing researchers to come to grip with thorny issues that have previously been dealt with only by handwaving, or that have not even been recognized." Designing a complex agent-based model, therefore, is equated with a compilation of literature review and theory refinement, though not in a verbal form (Sun, 2009).

Third, ABM allows researchers to explore and extend ranges of theoretical realms. When a researcher maps specific empirical findings, he or she might be likely to be steered into comprehensive understanding of the state-of-the-art in the pertinent field. ABM has the strength to cover an extended range of logical consequences derived out of a set of assumptions. In other words, ABM can serve to develop a consistent set of hypotheses from unexpected, partly expected, counterintuitive or surprising results, and thereby stretch out theoretical boundaries or working hypotheses for supporting empirical investigations (Fuller and Vu, 2011, p. 364). For the same reason, ABM leads researchers to draw up a big picture, lying beyond the marginal effects expected from prior assumption/condition changes – whether trivial, gradual or punctuated. It inspires scholars to assemble fragmented empirical findings and arrange them on an extended parameter space. These potentials carry weight when ABM is devised with empirical data.

Finally, ABM encourages researchers to analyze simulation results and infer causality systematically, when coupled with experimental design (Harrison *et al.*, 2007; Levitt, 2004). Simulating an artificial world on ABM with an experimental design can be a secure path to analyzing results of different initial conditions. In recent publications, for example, Scott *et al.* (2019) performed a virtual experiment that takes into account seven network attributes, which consists of population size, preference, policy uncertainty and three collaborative group attributes including group size and invitation selection strategy. In the experiment, they opted to control some conditions while varying others. The experiment arrived at outcomes that help readers figuring out effects of a certain condition out of complex simulation results. Similarly, Choi and Robertson (2019) drew three different scenarios of public goods games, all sensitive to the average level and variance of social motivation, made up of a "three by three by two" virtual experiment. By exploring the results of different experimental conditions, we can sort out effects of different agent properties and rules, and verify various theoretical propositions.

Key research themes

General social sciences. With the methodological potential of ABM espoused as such, we are ready to go to another important question raised: what to grow/simulate. Some early works took a population ecological perspective. Along this line, we can list up, in addition to the Schelling model, such works as "sugarscape" model (Epstein and Axtell, 1996), NK model (Rivkin and Siggelkow, 2003) and rugged fitness landscape model (Levinthal, 1997). The basic idea behind these models is that agents interact with each other and with the place they are located in, while pursuing their own goals. In the sugarscape model, agents are made akin to human beings alive in the food gathering economics era; in the NK model with the rugged fitness landscape, agents search for an optimal place for survival roaming across the landscape. The landscape changes continuously in response to agent action while simulating interconnectedness of the elements is active.

Another stream of ABM research heeded topics such as organizational learning, decision-making and structuration. For example, Cohen *et al.* (1972) developed the garbage can model. March (1991) depended on a work of simulation when devising a theoretical framework to examine exploration and exploitation as two modes of organizational learning. Carley's serial works (1991, 1992, 1995) on evolution of organizational structure and performance set a cornerstone in the field of computational organization theory.

Still more, ABM has proven useful in collaboration research. Axelrod (1997) simulated competition and collaboration to probe into evolution of new strategies, promotion of social norms and dissemination of culture. Bellamine-Ben Saoud and Mark (2007) applied an agent-based computer simulation to a new form of synchronous real-time collaborative engineering design. It is an attempt showing possibility of creating a visual artifact with cooperating agents interacting in a dynamic environment. Son and Rojas (2011) used ABM simulation to trace evolution of collaboration in temporary project teams. It shows the collaborative practices among heterogeneous individuals demonstrating varying work performance, depending on the number of individuals congregated to accomplish the project objective. Arvitrida, Robinson and Tako (2015) used ABM to model business competition and collaboration in supply chains. Their finding claims that the simple representation of a strategic landscape influences the competitive and collaborative behaviors in business.

Public administration research. Now, turning to public administration, we see only a handful of ABM employed research in the field. Seminal works are spotted in the field of simulation of collaborative governance and network. Johnston *et al.* (2011) published one of the earliest ABM works in the field. Their features centered on the effect of inclusion practices on stakeholders' expectation of each other's contribution and collaboration. Robertson and Choi (2012) and Choi and Robertson (2014a, b, 2019) published a series of ABM-supported theoretical articles. The mainline theme covered deliberation and decision in collaborative governance, focused on motivation, power and decision-making structure. More recently, Scott *et al.* (2019) performed a simulating study, dealing with stakeholder agreement in collaborative governance under varying conditions. In somewhat different vein, Maroulis and Wilensky (2015) applied an ABM method to investigate street-level implementation of innovation, drawing on organizational learning theory.

Outlook. Looking ahead for the areas where ABM could be fruitfully employed in public administration, we may wade through various disciplinary grounds. At this point, we have identified protruding mainline thematic topics centered on systemic inquiry into interactions between human behavior and structure. ABM opens a way to support this thematic pillar with the promise to improve relevant methodological frameworks and theoretical propositions.

First, as having been implied earlier, institutional analysis may gain momentum, when equipped with ABM (Siddiki *et al.*, 2019). The benefit would be to enrich theoretical body of institutionalism, capable to display connection between agency and structure. This is a demanding task. When successful, it could render a powerful model to demonstrate pieces of institutional concepts and languages integrated into a consistent theoretical construct.

Second, ABM offers possibility to expand investigative width of hybrid governance and allow predicting its performance. Scholars using ABM would seek varying forms of hybrid governance designed by different combinations of ownership, rewards and authority crisscrossing market and hierarchy (Makadok and Coff, 2009, p. 299). When effectively explored, numerous prototype devices can be brought out and diversify relevant theoretical expositions.

Thirdly, recent findings of representative bureaucracy argue that symbolic representation takes varying effects. It becomes manifest when expressed in terms of response of actors to values of trust, fairness and performance of the organization (Grimmelikhuijsen *et al.*, 2017, p. 52). To this end, ABM can be a serving tool to upscale learning models that have dealt with organizational diversity and performance.

Finally, network analysis regarding spread of information and knowledge, disease, and innovation has formed a large volume of research in the general computational field. ABM has the potential to regenerate, expand and put into scrutiny the relevant thematic arguments raised as they address the issue of the emergence and change of structure out of agent interactions. The potential would gain weight in public administration when bolstered by the accumulated or ongoing studies on spread of organizational reputation, corrupt behavior, policy idea or information and communication under crisis.

In summary, ABM has been in use for studies in wide-ranging topics. They range from population change, learning, adaptation, networking, decision-making to collaboration, particularly in simulating collaborative governance in public administration. The looming themes are inviting. It indicates disciplinary competence accorded on public administration research, made possible by access to the utilities of ABM. Not to mention holding a prominent outlook, ABM might be tapped by scholars in prevalent or prospective research on institutional analysis, hybrid governance, organizational diversity and network spread, to name a few.

Limitations of ABM and Mitigations

Limitations of ABM

In spite of the strengths associated with ABM as discussed above, it is important to note what ABM is not meant to be. This is particularly important for researchers who are about to embark on academic venture delving unexplored areas of research.

Relationship to empirical findings. It is noteworthy that simulation results from an agent-based model are by no means a substitute for empirical findings. Researchers may be inclined to discussing simulation results as if they were as real as seen in empirical findings. It is especially the case when seeking practical implications from the executed model. Simulation results, even combined with empirical data, are but an extension of logic. Researchers, therefore, should be careful when trying to extract practical implications from a simulation result-especially when exploring new areas of research in the absence of empirical evidence to verify the implications to ensue.

Even with the limitation exhibited, however, it may be noted that simulation results and empirical findings are complementary to each other in two ways. First, an agent behavior can be modeled based on well-replicated empirical findings as well as game theoretic logic. This in particular applies when a researcher probes into social psychological issues such as human behaviors in an empirical public goods game (Choi and Robertson, 2019). Second, propositions or hypotheses derived from a model can motivate empirical researchers to validate empirical findings, and add rich nuance to them. This is a feature and a potential of ABM to reinforce the conclusion derived from a study, and lighting up avenues for the future course of research.

Topic selection. An enticing motivation for researchers to approach ABM is to simulate *any* human and social phenomena. Logically, there is no limit to modeling social entities as far as the modeler provides a legitimate rationale. This does not, however, downplay the importance that a decision on what to model and on how wide a range to cover by the model should be made in such a way to reconcile the rigor of the model. First, some topics may be simply addressed by empirical research than by ABM. For example, whether people are better motivated by money, gift or compliment (Gneezy and List, 2013) is definitely in the realm of empirical research. Second, there are ethical issues involving mostly simulating human behaviors or prototypes of human society based on biased real-world data, which are often found in artificial intelligence-driven decision making. When defining an agent, for instance, researchers may be warned so that they avoid stereotyping a certain group of people. Also, researchers may need to be aware of the social implications derived from simulation results. Ethical issues become explicit when the model is designed specifically for controlling human behaviors.

It also noteworthy that the rigor of a model can diminish when one attempts to simulate too wide a range of social structure. It may be difficult and costly, if not impossible, to simulate communication patterns of the entire Department of Homeland Security. Simply put, there is no point to simulate exactly the real world, just like there is no point to survey all American voters to predict a presidential election.

The limitation in topic selection, however, should not be confused with pioneering efforts in scholars' fields of research. For example, emotion is a fascinating issue in general social sciences, from psychology to public administration (Hattke *et al.*, 2020; Levitats *et al.*, 2019). ABM researchers have a full reason to design a model to address emotion. In addition, there are human behaviors not simply driven by "computational" reasoning. We need to be fully aware of what it would ontologically and epistemologically mean to simulate emotion. It would be particularly so when devising a "computational" information-processing model, not to mention how one can actually design an agent of emotion or "irrationality."

Mitigating limitations

The limitations of ABM viewed from the ontological and epistemological standpoint may not be completely curable, as in the case of other methods with their own drawbacks. Nevertheless, we suggest several ways to mitigate the limitations to realize its promises to the best.

Mixed method approach. An effective way to mitigate the limitations of ABM is to design a mixed-method approach from the beginning. Using a mixed method has been on the rise over the past (Mele and Belardinelli, 2019). One way to the mixed method is to devise a model that can reproduce the data compatible with the empirical data, when deployed on the relevant macro-level structure/dependent variable (Epstein, 1999), then run the model with an extended parameter space to further develop a theory. Another one is to first devise a model and get a set of results from it, and then combine it with typical empirical cases that represent or enrich each type of results. One can even combine ABM with meta-analysis to scan and enlarge the picture of the research arena. Maroulis and Wilensky's work (2015) on social and task interdependencies in innovation is an exemplary work combining empirical data with ABM.

Extended use of sensitivity analysis. Sensitivity analysis is a standard, or often a routine required of articles employing ABM. It can be an effective tool when carefully combined with the mixed method. According to Epstein (1999, p. 52), sensitivity is about the effect of small changes in input such as initial parameter values on output such as performance of the simulated system. Although sensitivity analysis is considered to demonstrate the rigor of simulation results out of rather arbitrarily defined parameter values, more strategic uses of sensitivity analysis may add values to ABM.

For one thing, sensitivity analysis can enhance the chance for ensuring replicability. Although the recent academic practice asks authors to provide supplemental materials such as (pseudo-) code of their model in the article or a public website [4], the point is not so much to let other researchers run the same model with the same language. It is to replicate the similar-though the same theoretical insights held-results with different models coded by different languages and algorithms. Harrison *et al.* (2007, p. 1243) well put the point:

> [F]ailure to replicate a finding does not necessarily mean that it is wrong, however. It may be that the original finding holds only under certain conditions or only for certain ways of operationalizing the formal model.

Sensitivity analysis, in this sense, offers a sort of "confidence interval" from which to tell whether two or more different models are compatible with each other.

Multidisciplinary research projects. Contributions from ABM may be maximized when a researcher designs and performs a multidisciplinary research project that are not easily amendable to empirical research. Note that an agent-based model is built from a set of micro-level assumptions about agents and their interactions. It, then, simulates a macro-level structure theoretically expected to be linked with the former. As such, it is not surprising that social psychologists find ABM useful in interdisciplinary studies. Smith and Conrey (2007, p. 101) put it:

> One of the primary features of ABM is that it allows, even forces, theoretical thinking to cross levels, as modelers seek to understand high-level structures and processes as outcomes of low-level agent interactions. Thus, ABM provides a common framework for processes at multiple levels, making it a natural focus for cross-disciplinary integration.

Scholars often criticize that laboratory experiments are carried out in an isolated condition, making it impossible to investigate contextual influence (Borgatta and Bohrnstedt, 1974). Although ABM cannot substitute empirical experiments, it can still empower the contextual implications, offering a multi-level analytic tool. In this sense, ABM is an investigative muscle to buttress multidisciplinary research, which can move forwards to help behavioral foundation taking shape in public administration research.

AI and machine learning. Public administration research is not an exception in benefiting from the rich pool of public data and machine learning. The trend is in parallel with the rising interest in machine learning we see these days (Anastasopoulos and Whitford, 2019). Given that an agent is a stylized computational entity of human behavior, it would not be amiss to expect artificial intelligence technique and machine learning to meet with ABM. The congruence is expected to come in a near future and open up a new horizon of intellectual inquiry. The immediate venue would probably be in the task of researchers to design and "educate" agents to act more like a human being. It would be a dramatic shift exhibiting artificial intelligence algorithms, overriding the "manually coded" programs that simply follow a set of tailored rules.

Practical issues

In this final section, we share some of the practical issues in using ABM, whether in research or in writing articles. As stated earlier, ABM is not a method firmly established in public administration. Researchers interested in ABM may be better informed by the following discussions.

First, researchers need to learn programming language to design and run an agent-based model. There are tailor-made programming tools dedicated to ABM such as NetLogo (Tisue and Wilensky, 2004) and MAIA (Ghorbani *et al.*, 2013). They help researchers to easily build an agent-based model by combining existing modules built in the language. However, to get more degree of freedom in designing his or her own model, one may need to be familiar with more universal object-oriented languages suiting one's specific needs.

Second, it should be noted that developing an agent-based model is a stepwise practice. One may better begin with a simple model-easy to code, debug, and validate, then add new elements and complexities to the model. At some point in this stepwise process, the researcher may want to stop adding complexity in order to balance between different values innate to a theory, such as validity, tractability, transparency and parsimony.

Third, it is important to decide how to describe a model in a manuscript. Because the length of a manuscript is usually strictly limited [5], it is important to be concise and transparent in describing the model; whether it is verbal or figurative. Although it may seem efficient to present a flow chart or pseudo-code in the appendix, it has not always been the best way. As discussed before, the process of developing an agent-based model is equivalent to a process of theory search, integration and development. Therefore, each step taken in the model development has theoretical implications important enough to be lined up carefully with the main text. Simple figures would not be enough to deliver the more important part of the modeling. A group of prominent scholars have recently suggested the Overview, Design concepts and Details (ODD) protocol as a potentially effective standard to present a model for a better and efficient communication (Grimm *et al.*, 2020). The concept of ODD highlights that what should be communicated is the overview as well as details of the model and vice versa, and the way design concepts such as emergence, learning and interaction are used in the model. ODD also emphasizes that the structure of a model should be understood by "humans" and easily replicated (Grimm *et al.*, 2020).

Finally, as visualization methods have advanced these days (Evergreen, 2019; Yau, 2011), and the results of a simulation are rich and varied in terms of indices and dimensions, appropriate visualization technique is encouraged. For example, Scott *et al.* (2019) reported simulation results in an effective and efficient way by combining different charts in one figure to illustrate different results from multiple experiments at a glance.

Conclusion

In this article, we reviewed the potential of ABM as an alternative method to investigate public administration topics, especially addressing how ABM can contribute to theory development. To help readers to get the sense of what ABM *is*, we provided an overview of ABM, from definition, epistemological ground to building blocks. Then we moved on to address the potentials of ABM to contribute to theory development. The account was made both in terms of methodological advancement and of expanded research themes. The latter includes such themes as institutional analysis, hybrid governance, organizational diversity and learning, and network spread, to name a few. We next touched on the limitations germane to ABM followed by discussions on how to mitigate the limitations. We suggested four ways to guide us here – mixed-method approach, extended use of sensitivity analysis, multidisciplinary research topics and potential integration with artificial intelligence and machine learning. Finally, we made a short list of checkpoints to be observed when actually using ABM and suggested ways to facilitate communications.

In spite of the rising popularity in neighboring disciplines such as business administration, organization theory and psychology, ABM has rarely been accepted and used in public administration research. Considering the method in light of usefulness for theory building, the scope is still limited; particularly in a certain field where policy-oriented, practical approach may better to serve. However, when taking a careful glance at the realm of public administration, we may notice that the influence of ABM has taken shape as a new strand of investigative method. The influence has permeated into a growing number of fields such as organizational learning, adaptation, and innovation, complex networking behaviors, collaboration and institutional design. They have all proven well-suited research topics to go and mature with ABM. In this regard, this article reiterates its aim to encourage public administration scholars to get familiarized with the methodological attributes of ABM and come closer to the quest for the best path at their disposal to lead into theory building.

Notes

1. In this article, among several types of computational modeling, we focus on agent-based modeling. Others include cellular automata and system dynamics (Harrison *et al.*, 2007).

2. Note that it is not the intention of this article to give a manual-like guide to ABM.
3. Let's say that in the Schelling model, we add conditions to homophily such as income, reluctance to move after a certain number of iterations, and even random moves. This design would make the internal mechanism of the model more intractable.
4. See the CoMSES network for an example of such community (comses.net).
5. Public administration journals these days usually restrict the number of words to around 8,000, only with a couple of exceptions. It would be challenging to be concise and bring out all the details of the design and results within the prescribed space.

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