Evaluation and Program Planning 65 (2017) 131–138

Contents lists available at ScienceDirect

Evaluation and Program Planning

journal homepage: www.elsevier.com/locate/evalprogplan

Agent-based modeling as a tool for program design and evaluation

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ARTICLE INFO

Keywords:
Agent-based modeling
Systems
Complexity
Evaluation practice

ABSTRACT

Recently, systems thinking and systems science approaches have gained popularity in the field of evaluation; however, there has been relatively little exploration of how evaluators could use quantitative tools to assist in the implementation of systems approaches therein. The purpose of this paper is to explore potential uses of one such quantitative tool, agent-based modeling, in evaluation practice. To this end, we define agent-based modeling and offer potential uses for it in typical evaluation activities, including: engaging stakeholders, selecting an intervention, modeling program theory, setting performance targets, and interpreting evaluation results. We provide demonstrative examples from published agent-based modeling efforts both inside and outside the field of evaluation for each of the evaluative activities discussed. We further describe potential pitfalls of this tool and offer cautions for evaluators who may chose to implement it in their practice. Finally, the article concludes with a discussion of the future of agent-based modeling in evaluation practice and a call for more formal exploration of this tool as well as other approaches to simulation modeling in the field.

Agent-based modeling (ABM) is a powerful simulation modeling tool that has been applied in an increasing number of arenas in the last decade. Many evaluators, likewise, are intrigued by the opportunities this technique may hold for the field, and have published multiple pieces on how it might be employed for evaluation purposes (Chalabi & Lorenc, 2013; Israel & Wolf-Branigin, 2011; Morellet al., 2010). This possibility has become even more attractive as increasingly usable and affordable open-source software like Netlogo as well as public repositories of models, like openabm.org have made the technology more accessible to individuals without computer programming experience. Despite this increased accessibility and the growing calls for the use of simulation methods in the field, ABM has seen little to no use in evaluation up to this point.

This paper seeks to push this conversation forward by outlining the variety of evaluation-related activities that ABM could support. We begin with a brief review of key concepts in systems science and an introduction to agent-based modeling, positioning ABM as a method by which systems thinking can come to fruition in an empirical manner. We continue by integrating various recommendations made by practitioners in the evaluation field regarding how ABM could be used, organizing these propositions in the order of typical steps often taken in an evaluation process. We also explore the ways in which each of these suggestions might operate in an evaluation context by drawing on cases where ABM has been used in similar ways in other fields. Finally, we conclude with a call to practitioners to creatively but responsibly explore where such techniques could be beneficial to their evaluation practice.

1. Introduction to systems science and agent-Based modeling

In order to understand the benefit of using ABM for evaluation purposes, a basic grasp on how ABM works and its roots in systems science is necessary. *Systems science* is an approach to thinking about and studying problems as a function of their parts interacting as a whole (Meadows & Wright, 2008). Systems are often hallmarked by their non-linear behavior, which means that their outcomes are often non-intuitive, involve sensitive dependence on their initial conditions (e.g., the flapping of a butterflies wings in South America can shift weather patterns in China), and often include feedback loops (Patton, 2011). Feedback loops either balance systems, keeping them stable in a particular state or they reinforce the system, leading to exponential growth or decay in system outcomes (Meadows & Wright, 2008). Further, systems also have emergent properties, meaning that they have properties that arise from the interconnections among components of the system (i.e., the whole is greater than the parts) (Gates, 2016).

Many evaluators may be familiar with this idea due to its increasingly common use in the field; the American Evaluation Association even has a Topical Interest Group devoted to people interested in "systems"-related approaches. Despite the growing popularity of this concept in the field, many evaluators disagree about the definition of

*Abbreviations:*ABM, agent-based model(ing)

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http://dx.doi.org/10.1016/j.evalprogplan.2017.08.015
Received 6 February 2017; Received in revised form 22 August 2017; Accepted 25 August 2017

"systems" and what constitutes a "systems approach" to evaluation. A full review of systems approaches in evaluation is outside the scope of this manuscript see Williams and Imam (2007) and Gates, (2016) for an overview of systems uses in evaluation); however we will provide a few examples of how evaluators have incorporated systems into their practice.

Evaluators have applied systems science approaches for evaluation in a number of ways. Some evaluators have focused on the evaluand as itself being complex (Hargreaves, Cole, Coffee-Borden, Paulsell, & Boller, 2013). Viewing the evaluand as complex is useful for illuminating the relevant components to examine in an evaluation and can provide perspective to understand the non-linear processes through which the program may achieve its outcomes. Others take this further and approach the evaluation itself as a complex, systemic process (Patton, 2011). In cases where the evaluation approach is complex, evaluators incorporate systems thinking into their process for designing and implementing their evaluations. Developmental evaluation, for example, aligns its process with the changes in a program, creating a systemic evaluative response to a changing evaluand (Patton, 2011).

Still others have begun to introduce quantitative systems science approaches into their evaluation practice, including system dynamics modeling and social network analysis (Fredericks, a Deegan, & Carman, 2008; Honeycutt & Strong, 2012). Social network analysis focuses on patterns of relationships among actors in a network and system dynamics focuses on the role of feedback loops in understanding phenomena. These approaches allow for evaluators to measure the complex characteristics of their programs and to quantitatively explore contextual patterns surrounding the evaluand. For example, in evaluations using social networks, evaluators can measure the extent to which stakeholders are collaborating with each other, identify critical stakeholders, and follow the change in stakeholder relationships over time (Cross, Dickmann Ellyn Newman-gonchar, & Fagan, 2009; Honeycutt & Strong, 2012). Using system dynamics, evaluators can see the feedback loops surrounding a particular evaluand and how an environment with reinforcing or balancing characteristics may shift outcomes and impacts, for example.

While the field of evaluation has made great strides toward incorporating systems thinking into its practice, relatively little work has incorporated quantitative simulation approaches to understanding systems. There has recently been a call for evaluators to further consider the potential benefits of simulation approaches to build upon the ways that systems have been used as part of evaluation in the past. In particular, scholars have called for an exploration of agent-based modeling as a tool for evaluation (Israel & Wolf-Branigin, 2011; Morell, Hilscher, Magura, & Ford, 2010; Wolf-Branigin, 2013)

Agent-based modeling (ABM) is a system science method to simplify and simulate complex phenomena. From Epstein (1999) view, ABMs have several characteristics: a population of autonomous, heterogeneous *agents*; a spatial *environment*; and a set of simple local *rules*. The heterogeneous agents interact with each other and with their environment as the model iterates, and their interactions are guided by the rules that they follow. This means that there is not simply a top-down hierarchical structure guiding their behavior; the rules they follow are based on their localized interpretation of the world around them (however, it is possible for higher level forces to influence model behavior). The rules used by the agents are meant to be the simplest rules possible to generate the behavior of interest. The agents then generate macro-level phenomena from the bottom-up. ABMs are often discussed as part of a field of generative social science because the behavior of the agents creates the phenomena of interest. Where traditional statistical approaches obscure the contribution of individual differences to population-level impacts by focusing on *mean* behavior, ABM capitalizes on the interaction of individual behaviors to examine emergent, system-level behavior that would be otherwise largely impossible to see. In short, this approach is particularly useful for examining situations in which agents interact with each other or their surroundings.

To illustrate, let us consider a model created by Sissa (2015); further detailed in Sissa and Damiani (2015) that represents the diffusion of sustainable household resource (i.e., water, energy) usage practices. In this model, agents represent individuals in households who have a particular level of resource usage as well as attitudes about their use of resources. They exist in a bounded spatial environment with neighbors whose resource usage and attitudes can influence them as they create social norms. The model's rules dictate that, on each iteration, agents examine their neighbor's attitudes and resource usage behavior. Then, they modify their own (i.e., if they have a neighbor who very strongly believes in using as many resources as possible and exhibits matching behaviors, a more sustainable agent may choose to reduce their own sustainable behaviors and goals). Agents can also have several types of smart meters that give them different types of information about their resource consumption. These different types of meters can be conceptualized as interventions on agent resource consumption.

By allowing these agents to interact autonomously to generate emergent behavior, the diffusion of sustainable (or unsustainable) practices can be followed. This allows for studying the impact that different interventions might have on shifting population-level consumption outcomes. For example, implementing smart metering programs that give agents a real-time comparison of their energy consumption with their neighbors gives them more accurate information to consider when deciding on an appropriate level of resource consumption. Further, the model can facilitate the exploration of tipping points for interventions to target. For example, a particular level of diffusion of sustainable practices may be necessary to achieve large-scale decrease in energy consumption. By testing the model under a variety of conditions, one can observe those points where big jumps in outcomes occur. This example also demonstrates the strength of agent-based models for understanding non-linearity, as the model can help determine critical tipping points where we may see exponential growth or decay in the level of resource consumption among agents.

In addition, this example demonstrates the critical role that context can play in agent-based models. The modeler here has the power to include new policy initiatives that modify behavior. For example, if a utility company provides a particular type of feedback to users or a reward for achieving certain levels of consumption, the agents can change their behavior accordingly. Thus, we can see the impact of top-down changes in context. At the same time, we can observe the changes that emerge bottom-up from agents using their neighbors' behavior as a guide for how many resources they should consume. Further, unintended consequences may emerge from the model when examining the behavior change process. In this case, as agents receive feedback from their neighbors, they may discover that everyone around them has much higher consumption levels and in turn increase their own consumption (running contrary to the goal of the intervention). Understanding the particular circumstances in which these types of unintended consequences can occur may influence decisions about how to implement an intervention or help to understand how problems emerged post hoc.

Agent-based models are often created using the *modeling cycle*. This is an iterative process by which modelers generate questions, create hypotheses, choose variables and parameters, implement a model, and analyze and test the model. Then they begin anew with revised questions and hypotheses (Railsback & Grimm, 2012). Modelers often go through this cycle several times and engage a variety of stakeholder perspectives before they are able to generate a model that appropriately fits with the phenomena of interest that is agreed upon by all necessary parties. These models are often programmed in using software like Netlogo or the popular programming language, Python. There are many publicly available open source models, which allow modelers to avoid reinventing the wheel by starting with a model with similar features to their problem of interest and making minor changes, so it matches with their particular question of interest. For additional explanations of how models are devised, built, and used, see Wolf-Branigin (2013). The