Integrating Evaluation and Agent-Based Modeling: Rationale and an Example for Adopting Evidence-Based Practices

Jonathan A. Morell
Vector Research Center, TechTeam Government Solutions

Rainer Hilscher
Altarum Institute

Stephen Magura
The Evaluation Center, Western Michigan University

Jay Ford
Center for Health Enhancement Systems Studies, University of Wisconsin

Background: While there is a great deal of discussion about complex adaptive systems in the field of evaluation, little has been written about the expression of complex adaptive systems in terms of agent-based models, the execution of those models as computer simulations, or the tight integration of agent-based modeling with traditional evaluation methods. These topics need to be explored if evaluation is to move beyond using complex adaptive systems in an exclusively heuristic fashion.

Purpose: This paper advocates for the integration of agent based modeling into traditional evaluation activities. We advance this position in order to spark a movement toward incorporating the formal application of complex adaptive systems into the theory and methods of evaluation. To make our case, we provide a hypothetical example of how interactions between an agent-based model and evaluation can provide unique and powerful understanding about the adoption of evidence-based practices in the field of addiction treatment. We advance our argument by addressing four questions: Why combine evaluation methods with simulation methods? Why use a complex adaptive systems approach? Why add agent-based modeling to the mix of evaluation tools? What is the relationship between agent-based modeling and the theories and methods of evaluation that are being developed to deal with surprise, unintended consequences, and program evolution?

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Intervention: Not applicable.

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Data Collection and Analysis: Not applicable.

Findings: Not applicable.

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Evaluation has been trending away from linear, deterministic paradigms of program theory. Increasingly, there is recognition that programs develop and evolve over time, and that multiple system influences affect change along multiple interacting lines of causality. Because of this realization, evaluators have been developing methodologies to link program theory to program outcome under conditions of uncertainty. Morell (2005, 2010) has developed a framework for developing evaluation methodologies that are sensitive to unanticipated changes in either programs or their evaluations. The approach is based on degrees of uncertainty and complex system behavior. Patton (2010) has been developing the concept of "developmental evaluation," in which evaluation is cast as an unfolding process that must be sensitive to adaptation, unintended results, and side effects. The growing interest in systems views of programs emphasizes the implications of viewing a program as a system embedded in other systems, complete with overlaps, feedback loops, and nesting (Cabrera, Colosi & Lobdell, 2008; Wasserman, 2010; Williams, 2005; Williams & Imam, 2007).

The purpose of this paper is to further this conceptualization by proposing an integration of traditional evaluation methods and computational simulation methodology, specifically agent-based modeling. By "modeling" we mean an abstract computational implementation of a real system in which enough relationships are maintained to reflect a reasonable degree of real world behavior, but which strips out enough detail to allow the observation of relationships. By "simulation" we mean the process of running a model over time to study model dynamics.

Our advocacy of this approach is a result of collaboration among four people with diverse backgrounds. We are an organizational psychologist steeped in evaluation theory and method, a computer scientist with an expertise in agent-based modeling and complex adaptive systems, a sociologist with a deep background in substance abuse and mental health services, and an industrial engineer who has been active in promoting evidence-based practice in addiction treatment. The fact that it took collaboration among individuals with these diverse backgrounds to conceptualize this paper itself exemplifies what the field will need as it moves away from a focus on traditional notions of program theory.

To further this process we address three questions:

1. Why integrate simulation methods into traditional evaluation activities?
2. Why use a complex adaptive systems approach?
3. Why add agent-based modeling to the toolbox of existing evaluation tools?

Then we will provide an illustration of how our dynamic simulation-evaluation framework can be applied to the problem of evaluating the adoption of evidence-based practices in addiction treatment. Work presented here is a first step towards developing an integrated agent-based modeling evaluation system and provides only a conceptual implementation of such a system. Our goal here is to lay out in some detail the vision and mechanics of the proposed integrated system, and by so doing, to stimulate a community of interest within the evaluation field.

Why Integrate Simulation Methods into Traditional Evaluation Activities?

It is no surprise that programs change unexpectedly and that evaluators are skilled at adjusting to changing circumstances. The challenge, however, is adjusting while still employing powerful methodology. In the extreme, evaluation will always be able to accommodate to changing circumstance if the only methodology employed is a qualitative post-test only, non-comparative case study design (Shadish, Cook, & Campbell, 2002). In those circumstances there is no commitment to well validated scales that would require extensive time and effort to develop, no need to renegotiate for access to specific historical data, no advantage gained in tracking programs or people over time, and no need to recruit specific kinds of comparison groups. The only thing needed would be to change interview and observation protocols and to employ them as the evaluation unfolded. In short, there would be no sunk costs to write off and minimal reinvestment in adjusting observational and interview protocols.

But what to do if we are not satisfied with restricting ourselves to such a narrow methodology? What to do if we want a broader methodological pallet to draw from in the face of changing needs for data and data collection methods? At this point two concepts come into play—lead time and agile methodology. Lead time refers to how much time an evaluator has to change his or her design. Agile methodology refers to the inherent ability of an evaluation design to change. Lead time comes from program monitoring and observation while the program is operating. Agility is built into the evaluation design early in the evaluation life cycle. For an extensive discussion of how these concepts play out in practice, see Morell (2010). Agility and lead time are related because the greater the agility, the lower the burden on monitoring to maximize early indications of the need to change. Still, it is always true that the longer the lead time, the better. Simulation can be a powerful tool for generating advance hints of unanticipated program change.

How can simulation do this? It can do this by providing evaluators with insight on the range of possible program behaviors and outcomes that may develop over time, that is, the program's "performance envelope." "Program" refers to the assemblage of people and resources that are brought together in a coordinated fashion to achieve a stated purpose. We see the notion of "performance envelope" as a broad concept that includes both what a program is doing with respect to its expected behavior and also how the program may be changing in unexpected ways. Of course the simulation will be only an approximation because it will of necessity be based on a simplified model of reality. And the longer a simulation is run to predict future outcomes (the longer the prediction horizon), the less meaningful its predictions become and the greater the potential for uncertainty due to unanticipated events. Our proposed integrated system prevents such uncertainty accumulation by frequent boundary checks between the model and evaluation activities.

Because of the tight and organic integration of simulation and evaluation activities, simulation can function as a guide to collecting empirical data on program behavior. It can say to us: Given the best data we have, and the best program theory, and our best guess about the behavior of the program's environment, this is the array of behaviors we predict. While evaluators should not take a simulation's results as gospel, they can most certainly derive insight as to what might be happening, and more important, how their methodologies need to be changed in order to assess what might be happening. In other words, simulation can increase evaluators' lead time in anticipating how their designs and data collection schemes might need to be altered.

Using simulation to help understand the course of social and organizational innovation adoption is nothing new or radical. To take an example from a familiar field of operations, Hirsch, Levine, and Miller (2007) simulated the adoption of an educational reform involving curriculum change. Their modeling framework was "system dynamics modeling," an approach which relies heavily on the relationships between stocks, flows, and causal loops. By drawing on the best available quantitative and qualitative data, they were able to build a model that allowed them to test "what-if" scenarios of adoption as a function of variables such as experience with the innovation, trust between school and community, and teacher motivation.

Although the application of simulation to the study of systems and innovation adoption is common, we are advocating the next step, i.e. the inclusion of simulation as an ongoing element of evaluation designs, with continual feedback between traditional evaluation designs and simulation models.

We envision a scenario in which simulation informs evaluation design and data collection, while analysis of that data is used to improve the model on which the simulation is based. In a sense, we are advocating that simulation become a program monitoring tool that can provide leading indicators of likely program behavior. It can do this running multiple generations of program activity, thereby providing glimpses of what might happen over time. The process is depicted schematically in Figure 1 and proceeds as follows: (1) Research findings and expert opinion are combined to determine the most likely behavior of evidence-based practice adoption in a defined setting. (2) That knowledge is used to inform both a traditional, empirically based evaluation and a simulation. (3) Simulation and evaluation inform each other on an ongoing basis. Results of the simulation are used to alert the evaluators to processes and outcomes that may not have been expected (either in type or intensity), thus prompting changes in evaluation design or data collection. Newly collected data are then used to help the simulators improve their model. (4) The combined findings from evaluation and simulation inform new rounds of literature reviews and deliberations by experts. (5) The entire process repeats as the program proceeds over its life cycle and by so doing takes advantage multiple iterations of three feedback loops: (a) between expert opinion and the research literature, (b) between evaluation and simulation, and (c) between the combined output of evaluation plus simulation as well as the combined output of literature review and expert opinion.

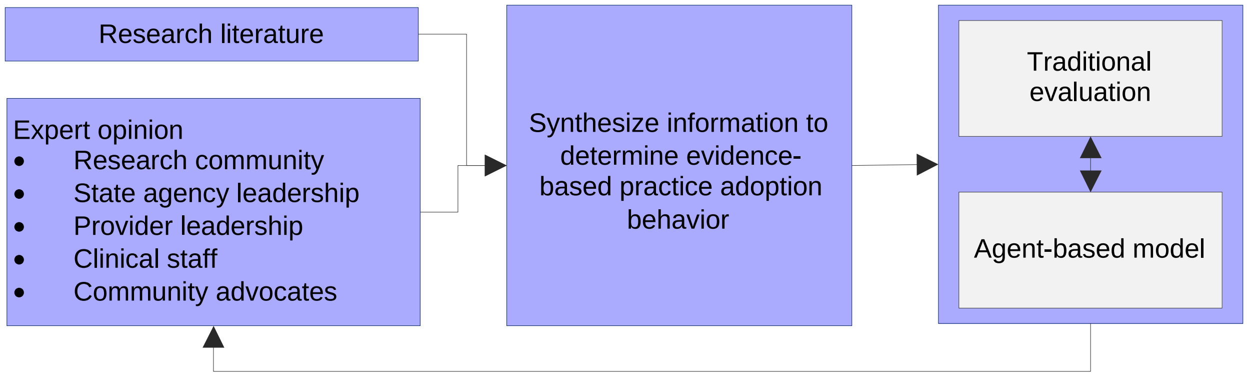

Figure 1. Schematic View of Integrated Evaluation/Simulation System

Why Use a Complex Adaptive Systems Approach?

In the previous section we defined a "program" in terms that entail a large measure of high level coordination. People are embedded in multilevel environments with social, cultural, economic, legal, and built environment components, to name just a few. Further, people are not the only entities that inhabit these environments. Schools, governments and companies are just a few of the myriad units that can nest and overlap with each other, and all can be decomposed or aggregated into yet other elements. As social scientists we have developed many powerful statistical tools to study and understand relationships in this complicated world. These tools have two things in common. First, most of them are based on models that attempt to identify important relationships (e.g., "correlations") and to simplify the relationships by ignoring or trying to minimize complicating factors. This is the essence of any statistical method based on the general linear model, in which main, interaction, and error effects are separated. The field has developed a set of tools and methodologies that are exquisitely designed to focus on some sources of variation set within the noise of other variation. Second, the relationships studied by these tools can range across long distances within systems. For example, we may study how children learn within classrooms, given how classes relate to schools, and how schools relate to local governments. We are good at looking at the world in this way, and we have gleaned a great deal of powerful and useful knowledge from our efforts.

But as we all know, the methods we have been using so successfully have severe limitations. No matter how good our designs, programs being evaluated continue to behave in unexpected ways that elude our ability to analyze, explain or predict. The problem is that the methods we have been using are incapable of dealing with the tangle of non-linear behavior that comes from phenomena such as intersecting feedback loops of varying latencies, or perturbations that ripple through networks of tight linkages, to name just a few. For instance, consider the phenomenon of rapid change. By employing the concepts of "attractors" and "chaos," complex systems science provides a theoretical explanation of why systems can exist in a stable state for extended periods of time and then rapidly shift either to a different stable condition or into a chaotic condition (Miller & Page, 2007; Mitchell, 2009).

Three essential features of complex adaptive systems make this approach strange to us: 1) emergence, 2) path dependence, and 3) an emphasis on individual behavior rather than average behavior. Emergence: Interactions between individuals living in local environments can result in non-linear cause and effect relationships on a macro level. These non-linear relationships result in emergent system-level behavior that is more than the sum of its parts. It is important to note that a consequence of emergent system level behavior is that it cannot be inferred from knowledge of individual behavior and of individual environmental features. Path dependence: "Dependence on initial conditions" captures the notion that previous states of a system limit the available states a system might take in the future. Or put in other terms, systems evolve along path dependent lines. As directions are set at one point in time, certain possible futures are opened and others closed. Individual behavior: In complex adaptive systems local variation can affect path dependent future states of a system. This means that all variation can matter in profound ways, which is quite a different perspective than the one with which we are familiar; that is, the sampling and statistical models designed to separate error from effect, and to compute normally distributed errors with a mean of zero.

Complex Adaptive Systems Applied to the Domain of Human Health

Multiple determinants of chronic diseases such as obesity and diabetes-2 constitute an example of emergent behavior (Diez Roux, 2008; Huang et al., 2009; Trickett, 2009). Determinants include genetic, epigenetic, neurobiological, , economic and cultural factors, as well as social network dynamics (Smith & Christakis, 2008) Although it is very likely that all of these determinants are implicated in causing chronic diseases across different communities of people, it is extremely hard to determine the exact relationships among these determinants. In one community social network effects might be the dominant factor, in another it might be cultural effects and in a third it might be the built environment (e.g., absence of supermarkets offering healthy food). Heterogeneity of people within communities, different environmental conditions and interactions between people and between people and their local environments, result in extremely hard to disentangle causal relationships driving chronic diseases.

An example of path dependence is policy resistance (Sterman, 2000). Policy resistance refers to the idea that new interventions might actually lead to unintended consequences instead of resulting in successful adoption. People may resist new behavioral rules they are supposed to adopt because these new rules may break the link between previously successful decision strategies and the environments in which these strategies were successful. Whether an intervention results in successful adoption or policy resistance can be seen as an instance of path dependence because adverse or conducive conditions at the time of the proposed intervention adoption strongly influence success or failure. Accordingly new interventions must be designed with fidelity in mind while taking into consideration the environmental conditions at the time the intervention is implemented. Using complex adaptive systems in this manner complements the kinds of methods advocated by Patton (2010) and Morell (2010), both of which are designed to maximize evaluation's capacity to understand and assess programs as they change over time.

Recent Complex Adaptive Systems Studies Relevant to Evidence-Based Practice Adoption

Recently, complex systems science has been promoted as a significant theoretical advance in a range of fields related to the evidence-based practice domain. Coming from an interventions perspective, Shiell, Hawe, and Gold (2008) and Hawe, Shiell, and Riley (2009) advocate the view that the current focus on "complex interventions" needs to be replaced with a focus on "interventions in complex systems." One of their main conclusions is that interventions in complex systems might take on different forms in different contexts without compromising fidelity. This is achieved by devising an intervention as a "series of events" that are adapted to the initial conditions of the context at the time the intervention is applied. Recognizing the difficulty of attributing causality in social epidemics with multi-level influences, heterogeneous social contexts and emergent social network dynamics, Galea, Riddle, and Kaplan (2009) present arguments that complex systems science is a powerful tool to study and predict the course of social epidemics using agent-based models. Taking a policy-making perspective on social epidemics, Hammond (2009) discusses the potential uses of complex systems science and agent-based modeling in aiding policy makers to devise policies that are better adapted to local contexts and dynamically changing social dynamics in heterogeneous populations. Finally, Paley (2007) applies complex systems concepts to a specific setting. He presents a complex systems analysis of a cardiac rehabilitation unit in a Scottish hospital. This particular unit had a very low referral rate from the hospital's cardiology ward; the underlying causes for this were unveiled as mismatched incentive policies between the cardiology ward and an attached respiratory ward.

Adoption of Evidence-Based Practice as a Complex Adaptive System

In light of the description of complex adaptive systems outlined above, it is easy to see why it might be useful to consider the adoption of evidence-based practice in complex adaptive systems terms. There are many heterogeneous actors—among them administrators, clinicians, supervisors, State officials, community advocates, and clinics. Remember, an agent only has to act in a rule-based way, not be a sentient creature. These actors engage in orderly interactions within their own social network as well as in interactions with actors belonging to other networks. There is an environment with characteristics affecting agent behavior. It is reasonable to believe that in all the hubbub of these interactions, both environments and agents will evolve over time. Admittedly it is a stretch to think of all these human actors as behaving according to only a few simple rules, or to think of complicated social entities such as clinics behaving likewise. But we hope that the explanation of complex adaptive systems and autonomous agents that we presented earlier has convinced you that it may be worth making that stretch.

Why Add Agent-Based Modeling to the Mix of Evaluation Tools?

So far we have discussed the value of simulation in enhancing traditional evaluation approaches and how a complex adaptive systems perspective adds deeper understanding to the study of interventions. Now we move on to advocating a particular genre of simulation, agent-based modeling. Traditional simulation approaches such Markov models proceed by identifying relevant system variables, estimating values for those variables, hypothesizing relationships among them, and writing equations that reflect those relationships.

A difficulty with traditional modeling approaches is the assumption that one can identify all the relevant variables "top down" and completely specify the relationships among them. To keep models mathematically tractable, many simplifying assumptions regarding model complexity need to be made. This is a particularly limiting requirement in the context of modeling complex adaptive systems where system-level behaviors dynamically emerge from individual interactions. In contrast, the "bottom-up" approach of agent-based modeling does not require that elaborate relationships among many system elements be quantified. From a modeling perspective, agent-based modeling takes the opposite approach by specifying explicit environmental conditions and individual agent decision rules. This methodology is ideal for the study of complex adaptive systems because local environments can be realistically simulated and individual agents interact with this environment as well as with other agents. Explicit implementation of decision making allows researchers to dip into the vast cognitive science and organizational behavior literature and equip agents with decision rules observed in real people. It is easy to generate heterogeneous populations of agents by varying certain state variables and selecting different decision rules. Path dependence and phase transitions naturally follow from the generative aspect of interacting agents because decisions made in the past preclude agents from making certain decisions in the future. Further, as small changes accumulate, a sudden switch to a different system-level behavior might occur.

In the above discussion people were described as being embedded in multi-level environments. An agent-based model allows the explicit modeling of different environmental domains. As an example, imagine a substance abuse treatment clinic that exists in an environment with changing reimbursement policies and changing population demographics. The model need not posit how other types of agents affect the policies or the demographics, but only that: (1) the changes occur in some particular way (randomly, at a fixed rate, or some other manner), and that (2) the agents can detect and react to the environmental changes. Since agents "live" in each of these domains, between- and within-domain non-linear feedback loops can be studied with agent-based models. Agent-based modeling makes no effort to estimate mean behavior on the part of a population of agents, or to impute their collective behavior to some distribution around that mean. Rather, it allows each individual agent to act according to its decision rules and state of knowledge; system-level behavior emerges from the agent-agent and agent-environment interactions.

This does not mean that random variation is ignored. It is quite acceptable in an agent based model to build a distribution around an agent's decision rules. For instance, imagine clinicians observing a demonstration of a new "best practice." One could build the following behavior into each agent's behavior. (1) Decide if the person doing the demonstration has a professional background like mine. (2) If he does, toss a weighted coin with a 70% probability of coming up heads. (3) If heads, adopt the practice. The reason that it is not 100% is because there may be other factors mitigating against adoption, for example, resources. Of course it is an open question as to whether the world really operates according to the principles of emergence, or whether it just happens to be a way of describing the world that matches empirical observation. We leave this debate to others. For now, all we need accept is that well-constructed agent-based models can be successful in representing reality.

A particularly powerful aspect of agent-based models is the possibility of running "what if" scenarios based on different parameter settings. The example we will present below involves the adoption of evidence-based practices in addiction treatment settings. We establish agents at the level of clinic, supervisor, and line clinician. We include parameters for the frequency of interaction among agents of different kinds and the latency of responses. What this allows is the study of innovation diffusion under different organizational cultures and inter-organizational relationships. The situation is as depicted in Table 1. Scenario 1 is a top down organization. There is rich communication from higher to lower levels and little communication in the other direction. There is also a fairly high degree of cohesion within levels of the hierarchy, as indicated by the rich intra-level communication. In contrast, scenario 2 is characterized by rich communication both within and across levels of agents, but still with minimal contact across clinic boundaries. Scenario 3 has rich inter-clinic communication, but each clinic is populated by isolated individuals and a top-down management structure.

Table 1
Mimicking Organizational Relationships Scenarios

Frequency of Communication	Scenario 1	Scenario 2	Scenario 3
Among agents at the same level	High	High	Low
Higher to lower level agents	High	High	High
Lower level to higher level agents	Low	High	Low
Among agents across clinics	Low	Low	High
Response time to communication			
Among agents at the same level	Fast	Fast	Slow
Higher to lower level agents	Slow	Fast	Fast
Lower level to higher level agents	Slow	Fast	Slow
Among agents across clinics	Slow	Slow	Fast

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The agents in such a system are invested with a variety of decision rules concerning whether they will move toward, or away from, a proposed new evidence-based practice. Some of those rules are governed by interactions with others in their work settings. By using agent-based modeling methods, it is possible to "virtually" test agent behavior in a wide variety of different organizational settings.

An Application Example: Adoption of Evidence-Based Practice in Addiction Treatment

So far we have advocated for integrating simulation into routine evaluation practice and for agent-based modeling in particular. In this section we present an example of how such an integration might work in practice. We are about to descend into considerable detail on the topics of innovation adoption, research on the acceptance of evidence-based practices, and agent-based model building. We are doing this because it is only through detail that we can convey a sense of the reality of what it means to integrate agent-based modeling and program evaluation. High level generalities are useful to frame the subject, but detail is needed to be convincing.

The detail to follow is based on our research agenda for understanding the adoption of evidence-based practices in addiction treatment. Our aim is modest; we hope to convince you that agent-based models can be a useful methodology for the evaluations of innovation adoption with respect to evidence-based practice in this area.

Track Record of Innovation Adoption Challenges

After several decades of intensive clinical research studies and demonstration projects, funded mainly by the National Institute on Drug Abuse (NIDA), the National Institute on Alcoholism and Alcohol Abuse (NIAAA) and the Substance Abuse and Mental Health Services Administration (SAMHSA), the addiction treatment field has developed a considerable number of evidence-based practices. Evidence-based practice is typically defined as "the practice of health care in which the practitioner systematically finds, appraises, and uses the most current and valid research findings as the basis for clinical decisions" (*Mosby's Medical Dictionary*, 2005). Sackett et al. (2000) proposed expanding this concept to mean integrating the best available research (scientific) evidence with clinical expertise and patient values (also see Eddy, 2005).

The Institute of Medicine (1998) identified major gaps between the availability of evidence-based practices derived from clinical research and their use in community substance treatment programs; see also Sloboda and Schildhaus (2002). We know a great deal about improving the quality of addiction treatment (Magura, 2000). Such developments have led to the funding of major initiatives to attempt to move research-based treatments into real-world treatment settings (e.g., the NIDA/SAMSHA Blending Initiative; Condon et al., 2008) and the Robert Wood Johnson Foundation's NIATx and Advancing Recovery programs, among others. There have also been a series of local studies of attempts to introduce specific evidence-based practices into standard treatment programs (Garner, 2009).

Although these initiatives have led to some real progress, adoption of evidence-based practices in clinical work continues to be slow and inconsistent (Garner, 2009; Guydish et al., 2007; Miller et al., 2006). New interventions may require 15-20 years before being incorporated into regular care (Boren & Balas, 1999). While hard figures for rates of adoption of specific evidence-based practices are generally unavailable, some research on this issue is striking. Knudsen and Roman (2004) determined that only one out of five outpatient treatment centers in the U.S. reported adopting naltrexone (an opioid receptor antagonist used to treat alcohol dependence). However, this still may overstate the utilization of this treatment, since only 2% of Veteran's Administration patients treated for alcoholism were provided with naltrexone (Petrakis, Leslie, & Rosenheck, 2003).

None of a national sample of addiction treatment program administrators reported using behavioral couples therapy (Fals-Stewart, O'Farrell, & Birchler, 2004). Even after programs participated in NIDA's Clinical Trials Network, the rate of adoption of evidence-based practices after clinical trials have ended is low. Of five sites that had the opportunity to adopt motivational interviewing or enhancement, one achieved adoption and one partial adoption. Of five sites that had the opportunity to adopt evidence-based methamphetamine treatment, none achieved even partial adoption (Guydish et al., 2007).

There is great variability in the degree to which evidence-based addiction treatment practices are used in the criminal justice system (Henderson, Taxman, & Young, 2008). Further, in a national sample of private treatment centers, each center used only an average of 5 of the 15 evidence-based practices assessed; moreover, the percent of eligible clients who actually received a given evidence-based practice could not be determined (Knudsen & Roman, 2004).

Barriers to evidence-based practice diffusion are not limited to an individual clinician's or organization's conscious resistance to adoption, but rather more generally to the observed "unamenability" (our term) or "absorptive capacity" (Knudsen & Roman, 2004) of a treatment system or provider for the recommended change—which may involve a variety of reasons and organizational sources that interact in complex ways. In sum, evidence-based practices do work, but there are considerable barriers to their adoption. Although interest in evidence-based practices among addiction treatment professionals is high (Haug et al., 2008), the end result has been that large amounts of federal tax dollars spent on clinical research remain inadequately leveraged by the treatment field.

The difficulties of disseminating evidence-based practices in addiction treatment have persisted despite a great deal of credible research on the topic. The findings of multi-organizational trials regarding diffusion of innovations have been mixed. Solberg (2000) and Mills and Weeks (2004) found that organizational "readiness for change" affects success. Ferlie and Shortell (2001) suggest that a multilevel view including individual, group/team, organization, and larger environment-system factors is needed to explain variations in success. Research by Chen et al. (2004), Fountain (1992), Greenhalgh et al. (2004), Pronovost et al. (2000) and Wang et al. (2004) found that factors such as executive leadership support, change leader attributes, change team composition, and clear, concise outcome metrics contributed to the outcomes of change projects.

Offender treatment programs that provided more evidence-based practices were community based, accredited, and network connected; had a performance-oriented, non-punitive culture; had more training resources; and had leadership with a background in human services, a high regard for the value of substance abuse treatment, and an understanding of evidence-based practices (Friedmann, Taxman, & Henderson, 2007). Additional results indicated that several State organizational characteristics were either associated with more evidence-based practice use or interacted with local organizational characteristics in association with evidence-based practice use: (1) systems integration at the State level was associated with greater evidence-based practice use; (2) State staffing adequacy and stability strengthened the association between local training and resources for new programs and evidence-based practice use (i.e., in States with better staffing, the relationship between training/resources and evidence-based practice use in local facilities was stronger); and (3) State executives' attitudes regarding the mission and goals of corrections tended to diminish the extent to which corresponding local administrator attitudes were associated with evidence-based practice use (Hendersom et al., 2009).

NIATx: Lessons Learned

For the present study we rely on experience from two major efforts to deploy evidence-based practices in addiction treatment: the Robert Wood Johnson Foundation's NIATx (see Appendix 2).

NIATx developed a process improvement model specifically for the addiction treatment field and continues to provide training and consultation in the use of that model. The model is based on Deming's (1986), Rogers' (2003) and Nolan et al.'s (2005) conceptualizations of continuous quality improvement and diffusion of innovations. Based on their experience, addiction treatment professionals from NIATx have identified attributes that distinguish *successful versus unsuccessful spread* (i.e., adoption) *of innovative process improvement practices*. These factors can be mapped onto Rogers' (2003) "variables determining the rate of adoption of innovations." Factors observed to be related to *successful* spread of innovative practices are listed in Table 2.

Table 2
NIATx Success Factors Mapped to Rogers (2003) Concepts

NIATx Identified Success Factors	Rogers Mapped Terms
Identifies weaknesses and processes to correct a key problem	high "relative advantage"
Is simple to implement; is a small, simple change idea	low "complexity"
Gives quick results	short-term "observability" in terms of "speed"
Reduces workload	high "relative advantage"
Can be quantified	high "observability" in terms of "visibility"
Is a team effort	multiple "change agents"

The NIATx model also focuses on "communicating" the change in practice, giving opportunities to view the practice in action (viewing the "relative advantage"), and on testing and adapting the practice trough rapid cycle change ("trialability" and "re-invention," respectively). Factors found to be related to *unsuccessful* spread of innovative practices are listed in Table 3.

Table 3
NIATx Failure Factors Mapped to Rogers (2003) Concepts

NIATx Identified Failure Factors	Rogers Mapped Terms
Attempts to adopt a practice not important to your customer	"incompatibility with needs"
Lacks preparatory investigation into the root cause of the problem	low "relative advantage"
Is hard to implement	high "complexity"
Gives results months rather than days or weeks after implementation	low immediate "observability"
Does not improve staff workload; is driven by research protocols	low "relative advantage"
Lacks staff buy-in	no "change partners"
Is too large in scope, with not enough resources	high "complexity" and low "trialability" due to costs

These factors, empirically derived from a large number of innovation diffusion engagements in addiction treatment, will help inform the design and content of the agent-based model we are introducing below.

Theoretical Framework for the Agent-Based Model

Rogers' (2003) theory of diffusion of innovation provides a framework to organize research findings and providers' experiences on evidence based practice adoption in addiction treatment. Our premise is that the theory's constructs could be operationally defined and programmed for an agent-based simulation. If we are right, the results of the modeling should comport with observations emerging from NIATx and Advancing Recovery. Specifically, elements identified as empirically associated with "successful spread" (adoption) and "unsuccessful spread" of treatment innovations can be interpreted as variables determining the rate of adoption, particularly the constructs of "relative advantage," "complexity," "compatibility," "trialability," and "observability," as indicated above (Rogers, 2003).

Thus far we have established a theoretical framework for evidence-based practice adoption, a set of empirical findings about evidence-based practice adoption, and a working relationship with experts who can work with us to reinterpret the findings based on results of an agent-based model simulation. While we are comfortable up to this point, we realize that before any actual simulation begins, it would be prudent to conduct an additional literature review and to do focus groups with a diverse group of experts. One aspect of the focus groups needs to be a search for expert consensus. A second aspect must be an effort to capture the diverse opinions that may lead to testing the model under different conditions.

Considering how fiercely experts can sometimes disagree with each other, we are inclined to conduct these focus groups by using a Delphi methodology. The reason for all this preliminary activity is to determine specifications for the initial model with respect to who the agents should be (e.g., clinicians, and/or clinic directors, and/or clinics), what should govern agent behavior (e.g., whether the agent has the skills needed to deliver an evidence-based practice), characteristics of the organizational setting (e.g., hierarchical or flat), and characteristics of the environment (e.g., reimbursement policies or training opportunities).

Characterizing the Agent-Based Simulation Model

Knowledge of evidence-based practice adoption and model building can be combined to develop an executable simulation. This is a well known process in which research literature and expert opinion are drawn upon to set a model's parameters. In any such simulation, adoption would not be seen as a passive process in which an evidence-based practice is dropped into a clinical system to spread as would a drop of ink delicately inserted into a glass of still water. In the real world evidence-based practice adoption is facilitated by programs which insert those evidence-based practices into social systems that are governed by rules of social and organizational behavior. What sets agent-based modeling apart is the nature of those parameters. In our proposed scenario, the rules are those of agent-based behavior.

Agents. The initial model should be built along treatment system boundaries, e.g. the kind of state-supervised systems that are common in the world of substance abuse services. So doing will have the model parallel the social reality of substance abuse services, and will have the additional advantage of allowing the application of Advancing Recovery's databases. With respect to the actual agents, we would begin with three categories (1) individual clinicians, (2) clinical teams (e.g., clinicians and supervisors), and (3) leadership teams (agency and program directors). Keep in mind that while the latter two types of agents are comprised of individuals, the agent unit is the team.

Environment. The NIATx/Advancing Recovery experience indicates the following factors must be considered as part of the environment of agents for evidence-based practice adoption: (a) breadth of influence that "Single State Agency" leadership may have over other pertinent State agencies (e.g., Medicaid), (b) complexity of State bureaucracies involved in change processes. (I.e., is a State's regulation and licensing function in the same agency as public human services procurement, contracting and/or policy development?) (c) concentration/dispersion of desired geographic target growth agencies/ Statewide coverage, (d) level and degree of motivation for change to implement the evidence-based practice models among participating State entities or provider agencies, (e) presence of existing data collection systems across the collaborative that lend themselves to regular and consistent data collection, (f) specificity about which State partnerships have defined their project aims, and (g) effectiveness of the State and provider partners in engaging clinical staff and patient advocacy groups in considering alternative means of treatment. It is certainly possible to think of agents who drive these characteristics of the environment by means of rule based interactions causing emergent behavior. Doing so, however, would greatly complicate both the model and the data needed to shape the model. Our belief at present is that the boundary we have delineated between the system and its environment is reasonable. Should results of the simulation and evaluation prove otherwise, however, the model can always be revised or expanded.

The discussion of system boundaries in the previous paragraph deals with a specific case. The general lesson is that there is an art to drawing system boundaries. In general there are three considerations as to where agents need to be defined and where there is only a need for conditions that agents can sense. First, consider the theoretical question of what constitutes a meaningful system to study. Second, attend to the matter of data availability. If there are no good data that can be used to determine a given agent's behavior, it is best to exclude such agents. Finally there is the matter of practicality. The greater the number of different types of agents, the more complicated the task of building the model. Resource availability does matter.

Time. Agent-based model**s** allow the introduction of different time scales in agents' reaction to stimuli in their environment. For instance, we might posit that clinicians react very quickly to perceived behavior by their peers, while clinical groups react much more slowly to perceived behavior by other clinical groups. Estimates of these latencies are important because they affect patterns of feedback interaction that can profoundly influence how agent behavior evolves over time.

Evidence-Based Practices. As discussed in the previous section, evidence-based practice innovations will differ with respect to the difficulty of their adoption as determined by the innovation characteristics delineated by Rogers (2003). However, the Rogers research tradition goes beyond the nature of the innovations themselves. It also touches on the relationship between an innovation and its environment. "Relative advantage" is the degree to which an evidence-based practice is perceived as better than the practice or therapy that it supersedes; "innovation complexity" is the degree to which an evidence-based practice is perceived as difficult to understand and use; "compatibility" is the degree to which an evidence-based practice is perceived as consistent with existing therapeutic principles and past experiences and needs of the adopters; "trialability" is the degree to which an evidence-based practice may be experimented with on a limited basis in a program; and "observability" is the degree to which results of an evidence-based practice can be made visible to those in the treatment system considering its adoption.

Finally, in addition to all of the Rogers' (2003) "perceived attributes of innovation," we are able to incorporate additional variables that Rogers' (2003) synthesis of the literature has identified as important in the decision to adopt, for example, type of innovation decision ("authority versus collective versus optional"); type of communication channels; and social (e.g., treatment) system beliefs, norms and networks.

Decision Criteria. By what criteria will agents act? For instance, an agent may sense his or her environment and perceive that his neighbors have adopted an evidence-based practice, or that his superior wants him to, or that training is available, or that the evidence-based practice challenges his belief about what is best for patients, or any combination of these factors. As modelers we will need to make choices about what we want agents to sense, and what responses we want them to make based on those perceptions. These choices will be based on empirical data and the consensus of experts, as described above.

Influence Among Agents. The essence of an agent-based model is its ability to reflect the behavior of a complex system by capturing the ways in which agents affect each other's behavior. Because these influences can vary in their strength, mutuality, and timing, it is possible to mimic a wide variety of organizational scenarios. One class of situations can be modeled by allowing agents to affect each other in either strong or weak ways. The influence may be symmetrical (e.g., weak in both directions), or asymmetrical (e.g., weak from agent 1 to agent 2, but strong from agent 2 to agent 1). These parameters in agent-based models can be used to mimic organizational realities, as shown in Figure 2. It shows three levels of agents (clinicians, clinician groups, and clinic leadership) in various arrangements within and across layers of the organization. Scenario 1 is a fairly traditional situation in which influence flows among all levels, but the strong relationships tend to flow down. In Scenario 2 there is a more cooperative structure, with more of a balance among the levels. Scenario 3 shows a radical case in which influence patterns flatten the hierarchy. Of course many other possibilities exist. We present Figure 2 only to illustrate the possibilities that can be emulated by changing parameters of influence among agents in the system, not a literal representation of the world.

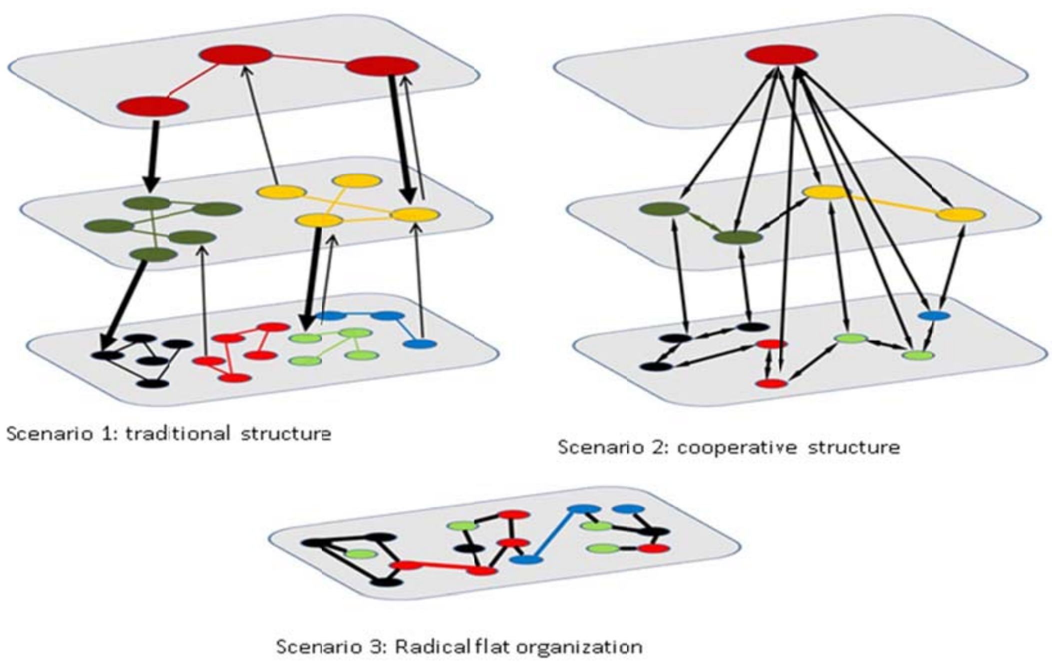

Figure 2. Examples of Organizational Patterns for an Agent-Based Model

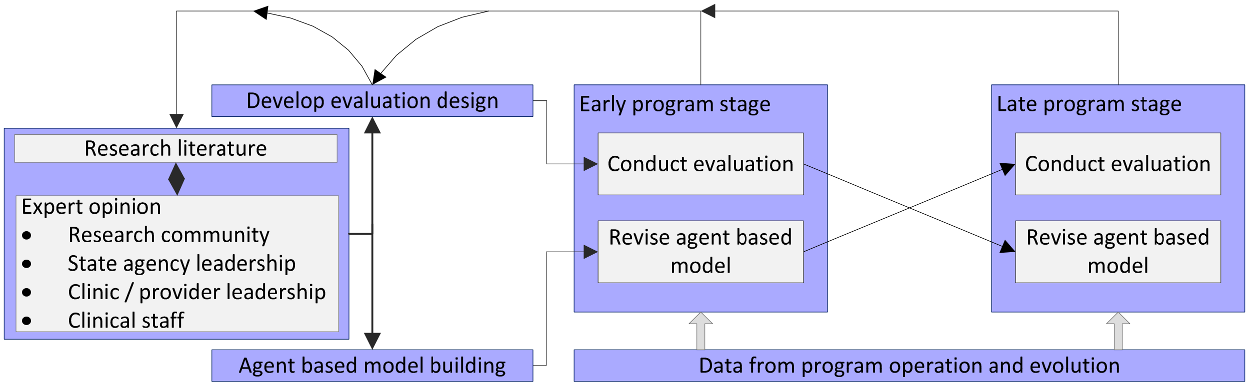

Figure 3. Detailed View of Figure 1

Conceptual Implementation of the Integrated Simulation-Evaluation System

The previous section explained how the model would be characterized. This section elaborates on how the model should be used. To help envision the process we present Figure 3, above, which is a more detailed view of the high-level depiction in Figure 1.

The process begins by choosing informants from within multiple stakeholder and expert groups—the research community, provider system leadership, and hands-on service providers. Similar choices are made with respect to relevant aspects of the research literature. Of course the groups and individuals chosen, or the bodies of research, may not be the right ones. (See further on for how these choices are corrected.) Based on the research and deliberations of the experts, a specific evaluation design is developed. A feedback process is placed between design and expert deliberations. This feedback loop takes the form of overlapping activities. In essence, the evaluation design team can be seen as part of the expert panel. Overlapping is needed because methodological considerations may affect opinions about what research needs to be considered. As a simple example, evaluators may inform the expert panel that a particular desired outcome measure would be very hard to obtain. That knowledge may prompt the experts to consider the value of substitute measures. Similarly, concurrence with expert deliberations is required for initial model building.

With the model and evaluation design in hand, both are implemented. Results may influence either the expert panel's deliberations and/or the evaluation design. It is at this stage where data may indicate a need to query new experts and/or to consider new bodies of research literature. Over time the model's output is used to influence the evaluation design and vice versa. The entire process is repeated over the program life cycle.

The arrows between "program" and "evaluation/model" are given a different form for a reason—they signify something special about the relationship between the program and the exercise designed to understand it. Programs are likely to evolve over time with changes in staff, client needs, funding, and regulatory environments. Program change is treated as an important input into the evaluation/model activity. In fact, it is precisely the fact of program evolution that is often the driver of unexpected outcome (both positive and negative), and it is the unique combination of evaluation and agent-based modeling that can provide evaluators with the lead time they need to adapt their designs to new circumstances.

Why does the integration proposed above lead to better evaluation? After all, in due course evaluators would have to deal with whatever unanticipated program behavior surprised them. And when the need arose, they would do a pretty good job adapting their measures and methodologies to the new circumstances. The problem is that the more the evaluators are surprised, the weaker will be their retooled evaluation designs. To take a few simple but realistic examples, a program may evolve in a direction that makes it desirable to develop a new measurement scale, or to negotiate access to a different comparison group, or to interview program staff at newly discovered critical time periods. None of this can be done well (or at all) if time is too short. The addition of agent-based modeling to traditional evaluation is valuable because it supports a variety of techniques that can increase evaluators' lead time in detecting surprises.

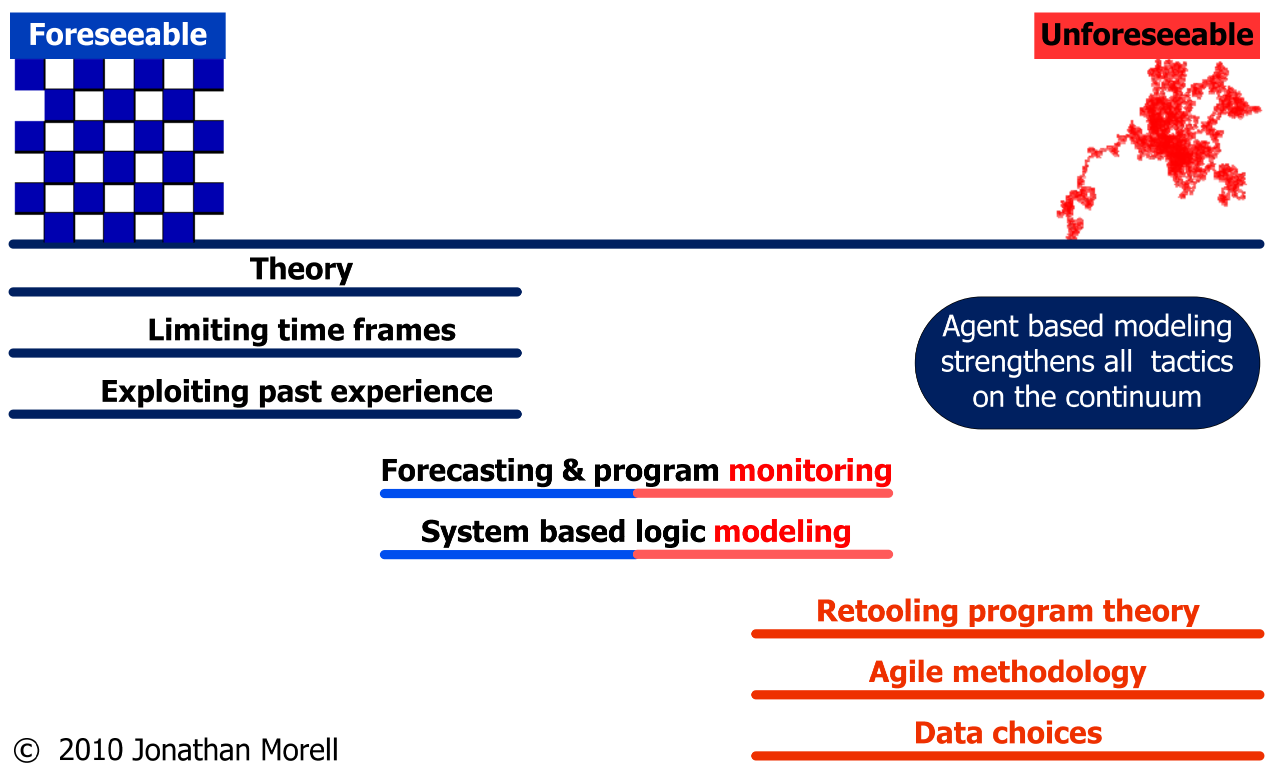

Figure 4. Methods to Deal with Evaluation Uncertainty

The situation is summarized above in Figure 4, which is an overview of Morell's (2010) framework for "evaluation in the face of uncertainty." In brief: There is a rough continuum ranging from unexpected program behavior that might have been anticipated (at least in general terms) to behaviors that are unpredictable because they are rooted in the dynamics of complex adaptive systems. Different tactics are useful along different parts of the continuum. In each case, invoking those tactics can lead to more perceptive and timely agent-based simulation, which in turn resonates through the feedback loops shown in Figure 3. For example, "exploiting past experience" is useful because many programs are developed without adequate attention to what happened to similar programs in the past: more attention, fewer surprises. The difficulty with this simple advice is that it is not so obvious what "similar" means; educated guesses have to be made.

By hinting at unexpected program behaviors, agent-based modeling may prompt experts to rethink what kinds of programs are "similar" to theirs. As another example, take the suggestion shown in the middle of Figure 4 to cast the logic model for one's program in a setting that includes other systems acting on the program of interest. This is a wonderful idea, but again, one that requires judgment as to which of the many possible candidate systems in the environment are worth attention. As with "past experience," agent-based modeling may reveal the need to consider a system affecting one's program that was not originally considered. Here also the suggestion would resonate through the feedback loops.

Conclusion

The reason to do evaluation is to provide valid information about a program's merit to interested parties. Evaluators' ability to fulfill this mission is often inhibited by a mismatch between the pace and direction of a program's evolution and the ability of their evaluation designs to keep pace with those changes. One strategy for overcoming this hurdle is to use agent-based modeling to discern a program's performance envelope over time. Doing so would maximize evaluators' lead time in anticipating and detecting likely program change. In this article we have advocated for an approach to realizing this strategy by means of a tight, iterative, and technologically sophisticated integration between empirical data collection and agent-based modeling.

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Appendix 1: Reference Agent-Based Models

Political Science Insurgencies (Bennett, 2008)

Models the early dynamics of insurgency using an agent-based computer simulation of civilians, insurgents, and soldiers. In the simulation, insurgents choose to attack government forces, which then strike back. Such government counterattacks may result in the capture or killing of insurgents, may make nearby civilians afraid to become insurgents, but may also increase the anger of surrounding civilians if there is significant collateral damage. If civilians become angry enough, they become new insurgents. Presents simulations of the dynamics of these interactions, focusing on the effectiveness of government forces at capturing insurgents vs. their accuracy in avoiding collateral damage.

GIS modeling (Jackson, Forest, & Sengupta, 2008)

Simulates residential dynamics in an area of Boston that has increasingly experienced gentrification in the past decades. The model is instantiated using basic empirical data and uses simple decision-making rules, differentiated into four classes, to simulate the process of residential dynamics. The model employs the consumption explanation of the cause of gentrification, which emphasizes the choices of individuals drawn to urban amenities, while testing the production explanation, which suggests that major investments from the public and private sphere attract and explain gentrification.

Organizational Modeling (Jiang et al., 2009)

Examines organizational adaptation on four dimensions: Agility, Robustness, Resilience, and Survivability. Paper analyzes the dynamics of organizational adaptation by a simulation study on the interaction between tasks and organization in a sales enterprise. The ‘what if’ analyses in different scenarios show that more flexible communication between employees and less hierarchy level with the suitable centralization can improve organizational adaptation.

Epidemiology (Perez & Dragicevic, 2009)

Presents agent-based model that integrates geographic information systems (GIS) to simulate the spread of measles in an urban environment, as a result of individuals' interactions in a geospatial context. Individuals in a closed population are explicitly represented by agents associated to places where they interact with other agents. They are endowed with mobility, through a transportation network allowing them to move between places within the urban environment, in order to represent the spatial heterogeneity and the complexity involved in infectious diseases diffusion.

Innovation Diffusion (Schwarz & Ernst, 2009)

Agent-based model of the diffusion of water-saving innovations. Studies the diffusion of three water-related innovations in Southern Germany. The model represents a real geographic area and simulates the diffusion of showerheads, toilet flushes, and rain-harvesting systems. Agents are households of certain lifestyles and use two different kinds of decision rules to decide upon adoption or rejection of the modeled innovations:

A cognitively demanding deliberate decision rule and a very simple decision heuristic. Thus, the model integrates concepts of bounded rationality.	
Epidemiology (Tawfik & Farag, 2008)	
Examines the effect of various awareness interventions on the spread of preventable diseases in a society. The work deals with the interplay between knowledge diffusion and the spreading of these preventable infections in the population. The knowledge diffusion model combines information acquisition through education, personal experiences and the spreading of information through a scale free social network. A conditional probability model is used to model the interdependence between the risk of infection and the level of health awareness acquired. The model is applied to study the spread of HIV/AIDS, malaria, and tuberculosis in the South African province Limpopo.	

Appendix 2

NIATx (formerly "The Network for the Improvement of Addiction Treatment"). NIATx was founded in 2003 with funding from the Robert Wood Johnson Foundation and the Center for Substance Abuse Treatment. NIATx developed a process improvement model based specifically for the substance abuse treatment field and provides training and consultation in the use of that model. The model is based on Deming's (1986), Rogers' (2003) and Nolan et al.'s, (2005) conceptualizations of continuous quality improvement and diffusion of innovations. NIATx began by providing technical assistance to 39 organizations. In 2009, NIATx works with more than 1500 organizations across multiple initiatives in all 50 states. At NIATx process improvement is defined as a series of actions taken by a change team to identify, analyze and improve existing practices within an organization to meet new goals and objectives. NIATx treatment improvement efforts focus on improving access to and retention in addiction treatment. The application of the NIATx treatment improvement efforts have resulted in significant and sustainable improvements in access to and retention in addiction treatment (Capoccia et al., 2007; McCarty et al., 2006; Hoffman et al., 2008).

Advancing Recovery (AR): State and Provider Partnerships for Quality Addiction Care is an $11 million national program of the Robert Wood Johnson Foundation, beginning in Sept. 2006, designed to promote the use of evidence-based practices by treatment providers through a series of innovative partnerships between providers and single state agencies. The 12 state-provider partnerships that have been funded in two separate rounds are: Alabama, Arkansas, Colorado, Delaware, Florida, Kentucky, Maine, Maryland, Missouri, Rhode Island, Texas, and West Virginia. This initiative is expected to improve clinical and administrative practices that impede the use of evidence-based practices. Selected grantees have implemented evidence-base practices from at least two of the following five targeted categories:

- The use of medications for specific diagnoses
- Screening and brief intervention in primary care settings
- The use of specific psychosocial clinical interventions
- The use of post-treatment aftercare
- Provision of case management, wrap-around, and supportive services

As we indicated in our literature review, there is much more to research on evidence-based practice than is contained in the NIATx and Advancing Recovery programs. Frankly, we chose these programs because of our personal working relationships with the leaders of these initiatives. Those working relationships are critical to our intent because our plan is ongoing interaction between those who collect data on evidence-based practice adoption and the performance envelope of adoption that is hinted at by the agent based models we will employ.