

# **“An ethnographic seduction”: how qualitative research and Agent-based Models can Benefit Each Other.**

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*Abstract: This note is a contribution to the advancement of social simulation as a method to model complex social behaviors with computational tools. We maintain that agent-based models would benefit enormously by the application of qualitative research (in-depth interviews, participant observations and extended case studies). We do this by providing a general analytical framework for empirically informed agent-based simulations and by assessing existing approaches to the instantiation and validation of models via qualitative data. We believe that this methodology would provide present-day agent-based models with a sound and proper insight as to the behavior of social agents – an insight that statistical data often fall short to provide at least at a micro level and for hidden and sensitive populations. On the other hand, simulations would provide qualitative researchers in sociology and anthropology (as well as to associated research fields) with valuable tools for: a) testing the consistency, and pushing the boundaries, of specific theoretical frameworks; b) replicating and generalizing results; c) providing a platform for cross-disciplinary validation of results.*

## **1. Introduction**

Qualitative research and formal modeling are often regarded as mutually exclusive. Qualitative – alternatively defined as ethnographic – methodologies provide rich and detailed descriptions of social phenomena based on propositional rather than numeric data, and can account for the meanings actors themselves give to their behaviors and attitudes. However, context-dependence and unrepresentative sample formation hinder generalization of results. In contrast, models provide simplified, abstract representations of reality in order to uncover the underlying structure of a phenomenon and to derive potentially universal conclusions.

Nonetheless, this article suggests that ethnography could be fruitfully combined with a particular approach to modeling, namely agent-based modeling (ABM) and simulation (Phan and Amblard 2007). This type of models take the form of computer programs simulating social processes, represented in terms of large numbers of autonomous agents that interact with each other over time. The primary aim of ABM is to assess the effects of micro-level behaviors on the social system as a whole; in this sense, it is particularly useful to account for social complexity emerging as an outcome of repeated interactions between multiple individuals, not of deliberate individual choices.

We argue that the specific nature of ABM (especially in comparison to other types of models, notably mathematical and statistical models), is especially suited for instantiation by qualitative data. This claim builds on an idea already put forward by simulation practitioners according to whom “there is nothing inherently quantitative” in agent-based simulations (Yang and Gilbert 2008: 175), despite their formal nature. Conversely, there is a growing awareness among qualitative researchers that “the world of agent-based modeling is

ethnographically seductive”. (Agar, 2003: 1.1). We explore the promises and shortcomings of bringing together ethnography and ABM, and provide evidence that advantages would be substantial for both sides. The range and general applicability of conclusions that can be produced by ethnographic methods would increase, while the accuracy of agent-based models and their capacity to meaningfully account for real-world phenomena would be reinforced.

In what follows, we provide background information on ABM and we review methodological arguments in support of its merger with qualitative research (section 2). Based on that, we go through three examples that offer different suggestions on how the two approaches may be combined (section 3). We then discuss the possible benefits, both for qualitative empirical research and for ABM (section 4). This material is then used in section 5 to outline a general methodological framework for coupling ethnography and ABM. Section 6 offers practical guidelines and some final remarks.

## 2. Defining ABM: what place for qualitative data?

A blossoming field of transdisciplinary research<sup>1</sup>, ABM uses computational techniques to simulate dynamic interactions between individual entities in a given social context. Emphasis is not on variables as in statistical models, but on “agents” (Smith and Conrey 2007) that are endowed with attributes and behavioral rules, and act on the basis of some decision-making criterion or heuristic – an epistemological posture sometimes illustrated by the catchy slogan “from factors to actors” (Macy and Willer 2002). ABM usually incorporates forms of adaptive or evolutionary change in that the individual decision-making process and the ensuing interactions between agents are iterated repeatedly and at each step, they modify the social context or environment; in some models, such changes lead agents to update their behavior (through processes of imitation, alignment on opinion leaders, social influence, etc.). This generates path-dependence, in the sense that past decisions and actions affect the current and future states of the system.

A key notion of ABM is that meso or macro-level regularities emerge over time from micro-level behaviors. Emergence enables recognition of social complexity by interpreting the target system as a whole which is more than the sum of its parts. Often cited examples of emergence – like the urban segregation model developed by Thomas Schelling (1978) in which a weak individual preference for race homophily in neighbors results in fully segregated neighborhoods – illustrate how individual behavior alone is insufficient to predict large-scale outcomes. Focus on iterated agent interactions and adaptive behaviors bridge “micro-motives” with meso and macro levels of analysis.

Emphasis on rules of interaction among agents instead of variables and social aggregates may render ABM an initially less straightforward choice for many statistically-trained social scientists. Nevertheless, this approach is fully in line with sociological theory and in particular, with the notion of social embeddedness in the sense of Granovetter (1985). Applications of

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<sup>1</sup> While the roots of ABM can be traced back to the 1940s, the methodology has established itself with the surge in computational power of the 1990s and 2000s (Gilbert and Troitzsch 2005). In particular, ABM has been greatly encouraged by advances in simulation languages and editor software, such as SWARM, RePast, Ascape, NetLogo, and Mason. A multi-disciplinary community of scholars has contributed to it, including not only social scientists but also psychologists, computer scientists, biologists and evolutionary theorists, and physicists. Wilensky and Rand (2007: 1.2) claim that “thousands of agent-based models have been published in the past few decades”. Indeed growing attention by the social science community has propelled pioneering publications like the *Journal of Artificial Societies and Social Simulation*, *Complexity*, or *Advances in Complex Systems* to prominence. It has also inspired several special issues of more generalist journals (*Social Sciences Computer Review* 2002; *American Journal of Sociology* 2005; *Journal of Business Research* 2007; *Journal of Economics and Statistics* 2008; *Journal of Internet and Enterprise Management* 2009).

ABM include, but are not limited to, the spread of languages or cultures, consensus formation in political debates, escalation of inter-group conflict, diffusion of technological innovations, collective use of land and natural resources, price formation in financial markets.

A summary review of ABM literature suggests that models fall into two main families, represented in table 1:

**Table 1 - Comparison between two families of ABM models**

“Pure” models	“Empirical” models
<ul style="list-style-type: none"> <li>• Built by abstraction from a target system (a social phenomenon or context).</li> <li>• Mainly regarded as tools for generating, expressing and testing theories (Moretti 2002).</li> <li>• Not always realistically representing choices and behaviors at the micro level.</li> <li>• Enable in-depth reflection on the possible unintended social consequences of purposeful individual actions.</li> </ul>	<ul style="list-style-type: none"> <li>• Open to estimation and validation via qualitative and quantitative data (Hassan et al. 2007).</li> <li>• Quantitative data can used to assess the probability that a certain event takes place within a given population of agents (Gilbert 2007).</li> <li>• Use of qualitative data to inform simulation rules and parameters is also attested since the late 1990s (Chattoe 2002).</li> </ul>

Models of the second type are certainly more palatable for those fields of social science in which abstract theorizing is less well accepted. The compatibility between ABM and both qualitative and quantitative data has led some eminent theorists to envisage multi-agent simulation as the “third way” in empirical research (Gilbert 2004). Various approaches to validation have been explored (Troitzsch 2004). Some of them are based on a comparison between outcomes of the model and (aggregate) empirical data:

- **Retrodiction:** the model should be able to reproduce a set of already observed stylized facts. For example a model of city growth and formation should reproduce the empirical distribution of city size (which follows a power law) (Axtell and Florida 2006).
- **Prediction:** the model should formulate expectations about the future state of a system. It is similar to retrodiction, but the empirical data will be collected and compared to the model *ex post*. For instance, a model of differential birth rates can predict the evolution of two different populations over time (Wilensky 1997).

However, this type of validity may be unsatisfactory as computer simulations produce sufficient, but generally not necessary, conditions for a macro-level phenomenon to emerge. Hence, a given micro-behavioral simulation might yield macro-level outcomes that fit with empirical data without this meaning that the model captures salient dimensions of a social phenomenon. In fact different combinations of parameters and initial conditions may be consistent with the aggregate trends of interest. Following Zeigler (1985) a third form of validity should be envisaged - one accounting for the micro structure of the model:

- **Structural validation:** the micro-behavioral features of the model should reproduce as closely as possible the characteristics of individual behaviors observed in the social context under study.

### 3. Three applications

For validation purposes, the use of quantitative data has been dominant so far; yet a growing literature is exploring the possibility to combine ABM and qualitative approaches. The following section reviews three examples that offer different suggestions as to the implementation of qualitatively-informed agent-based simulations.

#### *a. An ethnographer in Virtual Polynesia*

Drawing on her own participant observations in Western Polynesia, anthropologist Cathy Small (1999) designed *TongaSim*, a pioneering computer application simulating different kinship lines and marriage patterns within traditional Polynesian chiefdoms. This model aimed to provide an explanation to an apparently counterintuitive occurrence Small had witnessed during her fieldwork – namely that growing stratification did not result in a devaluation of women's status. In the absence of relevant field sources or literature, she used ABM to “grow” possible “social scripts” explaining how this outcome would come about. Observed social structures and customary practices were initially summarized into basic rules. The rules were subsequently used to inform the computer model and to conduct counterfactual experiments on familial settings that were traditionally conducive to high status of women. The iterative structure of the model allowed inferring explanations of how these settings might have been sustained over time and under various possible circumstances.

The model succeeds in showing that certain sets of micro-level conditions are sufficient to generate the macro-phenomenon of interest. It “explains” the data to the extent that it reproduces the observed fact while endowing agents with behavioral rules – that are applied uniformly to all agents and do not evolve over time – leading to marriage and family formation patterns consistent with fieldwork observations. It does not, however, involve the observed agents (actual Tonga residents encountered in fieldwork situation) in model validation. In this approach, the modeler acts as an external observer at a distance from the subjects under study.

#### *b. Evidence-based simulated warfare*

Contemporary internationalized conflicts display both conventional and civil warfare features. In particular, the lack of reliable statistical data as to army personnel records, casualties, etc. posits a challenge to social scientists. Armando Geller and Scott Moss (2008) used ABM to gain insight into the emergence of *qawm* — solidarity networks in Afghanistan with major repercussions on power structures, fragmentation of society, and ultimately conflict. In their model, agents' structural arrangements, behavior and cognition were informed by evidence and declarative data derived from case studies and interviews conducted in Afghanistan. The simulation results suggest that solidarity emerges systematically and leads to social segregation and substantial loss of wealth.

The empirical strategy is more sophisticated than in the case of Small, as two different sources of data are considered, namely the authors' own qualitative fieldwork and secondary network data. Qualitative interviews inform agents' micro-behavior and the local interactions of agents with one another, while the global pattern of emerging relationships (the simulated complete network) is compared to the empirical (secondary) network.

Agents' behavioral rules require each agent to form beliefs on all other agents, taking into account a variety of different dimensions for each of them (“endorsements”), and to update beliefs as systemic and individual conditions evolve under the effect of agents' own actions over time. This model is an example of how qualitative evidence can be used in concert with other data (namely network data) for cross-validation (Moss and Edmonds 2005).

### ***c. Companion modeling approach to natural resources allocation***

The “companion modeling” approach has been primarily developed to address social dilemmas and conflicts related to the collective use of natural resources such as land or water (see e.g. Barreteau and Bousquet 2000; D'Aquino, Le Page, Bousquet and Bah 2003). Stakeholders are involved in model-building at different stages and are asked to participate with their own knowledge and understanding of their social context. They provide information that contributes to shaping the model behavioral rules, attributes, and parameters. Validity comes from the solution being acknowledged by stakeholders as an acceptable one: it is a way to ensure that the model will be an effective tool for ensuring future cooperation.

By furthering an “emic” description (Headland et al. 1990) – i.e. one whose formulation is meaningful to social actors involved at each stage of modeling, both in the capacity of respondents and of stakeholders – this model pushes further the insider stance already adopted by Geller and Moss. Stakeholder participation is not limited to the observation/data collection phase, but it extends to the ABM-creation phase. In this sense this approach to modeling can be regarded as intrinsically ethnographic.

A potential limitation is that stakeholders may introduce biases and unduly influence researchers; conversely, the latter may manipulate the former. While these difficulties have been kept under control in the case of natural resource management, it is still unclear whether this can be extended to other situations. In addition, models with substantial stakeholder involvement are very context-dependent. This creates a tension between the need to represent the specificities of the situation under study and the potential for generalization of results which ABM brings along. Limited scope for cross-validation with other types of data and for accumulation of knowledge renders the identification of more general patterns of behavior relatively difficult.

### ***Comment***

The previous examples have been chosen in a growing body of literature. They demonstrate the vitality of a community of ABM practitioners combining qualitative methodologies and multi-agent simulation. A number of scholars, both trained primarily as field researchers (e.g. Agar 2001, Fischer 2006) and as modelers (e.g. Moss and Edmonds 2005) are presently adopting this approach. The three examples discussed pertained respectively to anthropology, political science, and natural resource management. Qualitatively-informed ABM is also of interest for sociology (Moretti 2002, Yang and Gilbert 2008) and social psychology (Smith and Conrey 2007).

Several options are available. The three examples outlined above interpret the relationship between model and data in different ways; adopt different understandings of model validity; opt for different levels of complexity in formulating rules for agent behavior; and finally, allow for different degrees of embeddedness of the observer in the social context.

However they all display three distinctive features which are crucial to our understanding of possible cross-fertilization between formal modeling and qualitative research. Primarily, they raise the question of how ABM may support the generalization of results obtained through the analysis of context-specific social data. Secondly, they emphasize the role of ABM in facilitating thought experiments and in enhancing theory generation within “grounded” qualitative researches. Thirdly, by providing insight into the social processes under study, they help counter the “black box” criticism often directed at computer simulation. These three points will be discussed in more detail in the following section.

#### 4. Advantages of combining qualitative research and ABM

When conjugated with sociological or anthropological techniques, multi-agents simulations enable to overcome certain shortcomings usually associated with the use of qualitative data.

Purposive (non-random) sampling accounts for the typically narrow size and limited representativeness of observed populations in researches adopting ethnographic methodologies. Moreover, context-dependence and reliance on declarative data to express subjective attitudes, preferences and perceptions may introduce substantial biases. The difficulty to generalize restricts the applicability of qualitative research as a basis to understand society and guide policy. Even in cases in which the entirety of a target population is interviewed or observed (e.g. small organisations or rural enclaves), conclusions cannot consistently be extended to cognate social structures – or to the very same social structure at other moments in time.

Although social sciences have occasionally known attempts to prove the generalizability of research findings and results (Yin 1994), research entirely based on case studies or ethnographies has traditionally fallen short to produce universally applicable claims. The absence of conclusive experimentation techniques and of extensive testing of the premises governing the data sets can be held responsible for this lack of generalizability. Nevertheless since the 1990s, computer-intensive techniques have successfully strengthened qualitative research not only by enabling formation of larger samples and management of larger datasets, but also by developing consistent codes and procedures to retrieve relevant information on specific topics. Also in fields other than simulation, the reliability, validity, stability and replicability of qualitative findings can be considerably increased as digital data processing and methods ensure that the hypotheses formulated by social scientists are really “grounded in the data” and not based on highly uncharacteristic one-off incidents (Kelle 1995).

Of course, this does not mean that – on account of the introduction of computer-intensive techniques – qualitative research does or should borrow notions of validity and reliability from unrelated research traditions. Although qualitative and quantitative data are, to a certain extent, mutually translatable with appropriate coding procedures and documentation, qualitative data are usually associated with social constructionism and often, though not always, distinctively limit the use of hypothetico-deductive reasoning in favor of inductive logic (Agar 1999).

As far as it fully respects the epistemic specificity of qualitative research, ABM can be used as a tool to perform “thought experiments” to test the consistency of social theories. As explained in Agar (2003: 5.2) an agent-based model is neither a tool to *perform* the ethnographic work, nor to *represent* it. Its use is rather limited to testing “a critical piece of the structure/agency puzzle” after qualitative data is collected. (It was precisely in this sense that the previous section illustrated how Small (1999) used ABM to complete her explanation of observed social processes in Polynesia.) In this perspective, ABM allows to perform counter-factual experiments, that is, to compare observed phenomena to simulated alternative scenarios in an effort to identify the precise role of each condition or hypothesis in yielding a given result (Chattoe-Brown 2002). By testing whether and when a given outcome ceases to appear, it allows extracting potentially universal patterns of behavior from the observations<sup>2</sup>.

Sure, Agar’s position does not cover all possible approaches to qualitatively-informed ABM (e.g. it does not accurately represent companion modeling). But it does have the advantage of drawing attention to the strength of multi-agent simulation as a tool for *theory generation*.

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<sup>2</sup> For instance, Rouchier and Tubaro (2009) studied consensus formation on a professional network, within a rigid hierarchical structure reproducing data from an organization. When subsequently hierarchy was removed from the model, its outcome showed little changes. This suggests that network properties matter more than the specific hierarchical arrangement, and that similar outcomes might be found in a wider range of organizations.

Simulation results may also suggest new questions for the fieldwork, and contribute to completing and improving the data collection. In particular in grounded theory, they can support “theoretical sampling”. In Glaser and Strauss’s (1967) definition, the latter can be described as a methodology to select new cases or observation sites, where the researchers saturate on a category and then move on to other categories. In this context, ABM can be employed to generate simulated ethnographic data in order to maximize varieties and differences in properties and attributes of social processes; subsequently, this helps defining and applying categories for interpretation, typification, and negotiation.

ABM provides a time-effective and cost-effective tool to achieve this; the iteration of observations can be pursued through the artificial generation of new “fields” or “populations” allowing comparison with the initial one. With agent-based simulations, replication of the characteristics of the initial population is also possible in order to assess sensitivity to small differences. In other cases, ABM enables to describe highly diverse groups from the target population, to magnify strategically meaningful similarities and broaden the scope of the observation. If in grounded theory the researcher is “the active sampler”, in ABM this activity is mediated by a computer software that generates different cases and supports the emergence of a theoretical framework by detecting properties, similarities, typologies, and scenarios.

Finally, it should be mentioned that ABM might be useful as a guide for policy-making. It may help to simulate possible forms of policy interventions *in silico*, before tests in the field are actually performed in order to make predictions on their possible outcomes, or even as a substitute for them in cases in which they are too costly, practically difficult, or legally and ethically questionable (Lempert 2002).

This combination of formal modeling and qualitative research is not a one-way alliance which only enriches the latter. On the opposite, it is a mutually profitable partnership that also provides ABM with increased opportunities for informing simulations and improving consistency with their target systems. The “naturalness” of multi-agent simulations as ontologies or representational formalisms for social science (Bankes 2002) can indeed profit from a deeper insight into behaviors, motivations, and relationships of social agents. In all the three cases presented in § 3, the use of rich qualitative data is meant to ensure saliency of the modeled behavioral rules and structures of interaction. Embeddedness of the observer in the social context (at one or many phases of the research) develops tremendous insight into the social processes under study. In this sense, it helps to counter the “black box” criticism that social scientists often address at computer simulation, fearing that despite control of the inputs and outputs of the model, the researcher might have limited understanding of its inner workings.

Indeed by providing “thick descriptions” of behaviors on the micro-level, qualitative-informed ABM achieves a clearer, more relevant and more understandable description of social structures and processes. It does so by improving micro-validation (referred to as structural validation in § 2). While theoretically a model always can be made to reproduce a certain real-life result, in the absence of a precise understanding of individual behaviors and motives this reproduction bears little or no explanatory value. What’s more, it may be difficult to compare to previously existing theories and findings. To ensure that the model reproduces relevant social processes and to allow cumulativeness of knowledge in social sciences, the design of behavioral rules for agents should be informed by detailed microdata, also including information on modes of inter-individual interactions and the conditions under which they occur. In this respect, qualitative data come particularly useful in their well-known richness and depth.

To be sure, quantitative microdata from surveys or administrative sources could also be used in principle. Even so, they are not always available, and not always accessible in sufficiently detailed form. In extreme cases, such data are utterly inexistent or unreliable: for

instance in conflict societies, such as Afghanistan in the aforementioned study of Geller and Moss (2008). Similarly, statistical data often lack for “extinct” social behavior and for hidden populations or hard-to-reach, socially sensitive groups such as drug users, sex workers, the homeless, subcultures and underground milieus (Agar 2001). The advantage of qualitative fieldwork is that it can often be done even in these situations, and suffers from fewer limitations than other forms of data collection. Particularly when participation of stakeholders is called upon in the search for a solution in companion modelling, the likely effectiveness of policies is increased by ensuring that the affected groups understand them and behave cooperatively. As a result, the capacity of social research to inform policy-making is enhanced.

## 5. A general framework for qualitatively-informed ABM

If ABM and qualitative research can potentially benefit each other, what epistemic and methodological structure enables articulation between the two to occur? This question underlies the more general inquiry as to the existence of a broad interpretative framework to develop qualitatively-informed ABM, despite variation in existing modeling approaches. To address these questions, let us first introduce two diagrams schematically illustrating the differences between traditional qualitative research designs and “pure agent-based models” (as described in Table [1], § 2). We will then proceed to characterize the qualitatively-informed ABM approach.

Leaving aside some nuances and qualifications, it can be said that qualitative research (fig. 1) typically proceeds from a given social process to the formulation of hypotheses which in turn assist the preparation of an agenda for data collection<sup>3</sup>. The empirical data collection (in-depth interviews, focus groups, participant observations, etc.) is followed by data analysis and theory generation aimed to represent/explain the social process under study. If limited to a loop from social process and back, statistical techniques might follow the same logic, thus ascribing the distinction between qualitative research designs from quantitative ones merely to the specification of the data collection methods. The introduction of a sub-loop (dashed arrows) is hence necessary to represent a distinctive feature of qualitative research, the repeated adjustments of categories and concepts to observed data (as well as, in some cases, the selection of new populations or new contexts of observation if suggested by additional pieces of evidence). This process is less emblematic of quantitative research, where categories typically pre-exist the data collection.

“Pure” ABM (fig. 2) abstracts a computational model from a social process of interest. In the absence of empirical data, understanding of this social process relies entirely on some already existent theory acting as an exogenous inspiration for the modeler – more than as an actual target system. Theory can thus be considered as the first stage for simulation-based research. After the model is designed and built, it needs to be verified and debugged by a suite of tests (Kefalas et al. 2003.) This of course means a fine-tuning of the initial model (dashed arrow) until it is operational. Sensitivity analyses may also need to be performed. The model

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<sup>3</sup> This is only in apparent contradiction with the “tabula rasa dogma” proposed by some qualitative scholars – specifically by followers of grounded theory. Famously Glaser and Strauss (1967) insisted that researchers should have no pre-conceived ideas or hypotheses when starting data collection. Even without taking into account the huge criticisms this position has generated over the years, we hereby rejoin the position of Allan (2003) according to whom this would be a misconception of the original premise: Glaser and Strauss were not actually advocating unfocused investigation, but rather giving a general warning as to the necessity to problematize preconceived ideas, ideological and personal biases rooted in the researcher’s mind. Grounded Theory’s tabula rasa should then be interpreted as a “working awareness of bias” which is a general rule in any interview-based research.



is then ready to be run to produce simulated data, which in turn is analyzed and interpreted so as to generate theory consistent with the built-in assumptions about the target system.

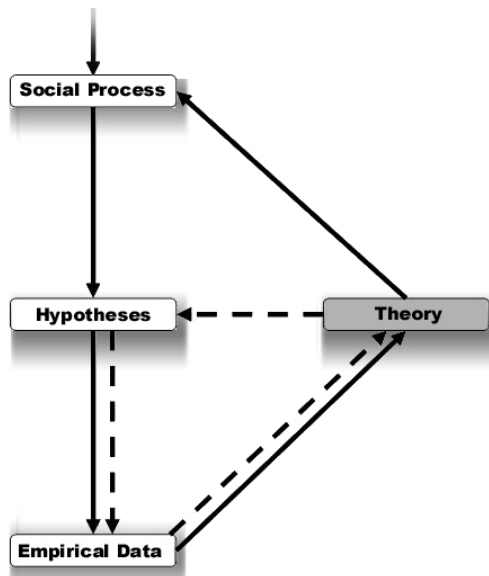


Figure 1 – One main loop and one sub-loop: the logic of qualitative research

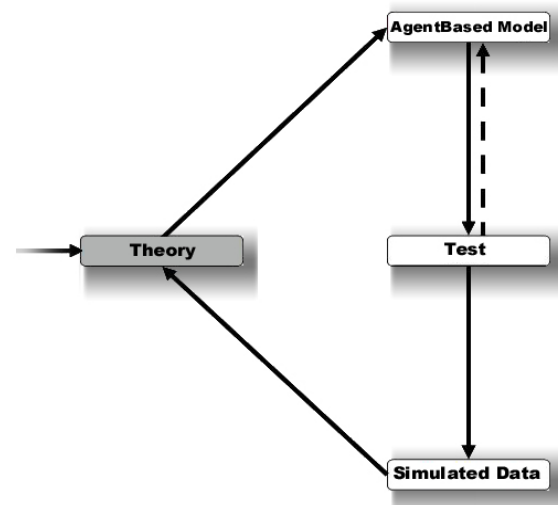


Figure 2 – One main loop with a fine-tuning phase: the logic of “pure” ABM

The use of ABM in conjunction with qualitative fieldwork (fig. 3) combines the different steps that are constitutive of these two research approaches. The diagram has a characteristic butterfly shape, where the two “wings” represent the main loops described in the previous figures. Like in qualitative research, the starting point is in an actual social process. After formulating research hypotheses and collecting empirical data, the already described sub-loop of category adjustment is activated, at the end of which a theory is produced. From there, an ABM is designed and built. After its verification and correction (fine-tuning), it can be used to create simulated data that are in turn analyzed to produce a new version of the theory emerging from qualitative data. This may either conclude the research or direct back to the sub-loop in the first “wing” by indicating the need to go back to the field. In turn, new empirical data may also suggest revisions to the agent-based model, and so forth, for as many times as needed. In principle, there can be a two-way feedback: from data to model and from model to data.

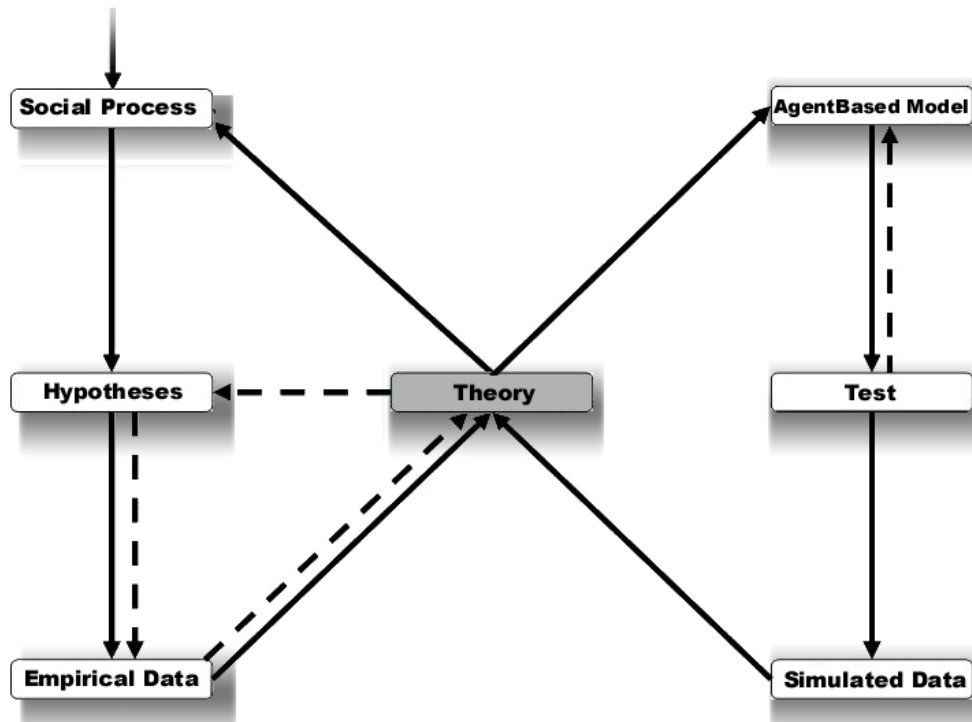


Figure 3 – A characteristic “butterfly” shape: the logic of qualitatively-informed ABM

The above framework allows qualitative data to intervene at different stages of the modeling process. A common feature of the three afore-mentioned examples is that qualitative research informs the model-building phase and helps define research questions, identify individual behavioral rules and modes of inter-individual interaction, and design scenarios to be simulated. In some cases, it also provides insight into how to amend them subsequently if necessary. Finally, it can be involved in the data analysis phase as well, to compare results from simulations and fieldwork, address any inconsistencies, and possibly help prepare a return to the field or a revision of the model.

This is therefore to be understood as a very general, overarching outline that allows for variation depending on the specificities of each particular research design. For instance in relation to the examples outlined in § 3, the researcher may not need to go back to the field after an ABM, as in the case of Small (1999). When a return to the field is due, the population under study may be involved at differing degrees and may be more or less aware of model structure and simulation results; in this sense, the above scheme covers both companion modeling and weaker forms of stakeholder participation. Finally, this framework does not preclude use of complementary sources of data for cross-validation as in the case of Geller and Moss (2008), should simulation results or fieldwork conditions require so.

## 6. Concluding remarks on transdisciplinary research

The previous sections have focused on existing applications of qualitative research to agent-based model-building. Attention has been called to different approaches, and the mutual gains of combining these two methodologies have been discussed. Finally, we have represented the logic of mixed research designs, bringing together multi-agent simulations and qualitative techniques, and included them in a general framework. This concluding paragraph is devoted to possible areas of development for qualitatively-informed ABM.

Our main intention here is to suggest that – despite a promising beginning – the application of multi-agent simulations to qualitative research is still limited to a restricted number of applications. The three examples we have presented go over three of the main uses of qualitatively-informed ABM: ecology, political sciences and anthropology. Others, mentioned *passim* in the preceding sections, are notable as well: public health, archeology, marketing, and economics at large. Although exciting, these applications need to be interpreted more as experimentations with a promising methodology than as the creation of a new research field – to say nothing of a new paradigm. In order to reach a critical mass of studies adopting this stance, new and diverse applications are needed. Emphasis, in this phase, should be put on encouraging a wider *variety* of applications, to new research fields and topics. From the arts to computer-mediated communication, from psychology to media studies, there is still potential for development. Diversification in application of qualitatively-informed ABM would deploy the full capacity of computational social science. After all, the social theory have been heavily influenced by artificial intelligence techniques and computer science both on a conceptual and on an empirical level. Truth is so far this influence has manifested itself mainly in the combination of quantitative techniques and computer science tools.

Although consistent with a path social sciences have already embarked upon, the diversification of applications of ABM to new topics in anthropology, sociology and psychology (as well as to philosophy and cultural studies) is a challenging venture. A certain number of “barriers to entry” still exist and appear difficult to go through for both ABM practitioners and qualitative social scientists. Among them, it is worth mentioning the need to fill in a noticeable competence gap that still nowadays separates computer- and mathematic-savvy modelers from humanities-oriented and fieldwork-experienced qualitative researchers. Such disparity has a decisive weight in research project design, mixed-team coordination, funding, publication strategies, scientific visibility and – more pragmatically – scientific careers. These issues account for the fact that transdisciplinary research agendas or researcher profiles integrating the two competencies in a well-balanced manner are still inadequate in both number and quality.

Even in the presence of a unifying framework, qualitatively-informed ABM as a research praxis stands nowadays on shaky grounds. The competence gap, though pragmatically-motivated, reveals itself also in the form of a certain “cultural dissonance” between experts in the two fields. For practitioners of both “pure” and statistically-informed ABM, “moving away from numbers” (Yang and Gilbert, 2008) can be rightly considered as a hazardous shift. Dismissals of qualitative research as “lacking precision” or as flawed by quasi-anecdotal evidence are still customary. Despite the half century-long efforts of social scientists to develop rigorous methodological guidelines and to formulate appropriate strategies for data collection and analysis (eg. Burawoy 2009), the use of qualitative data to validate models is often regarded as – at least – injudicious.

Respectively, the reticence of many qualitative researchers to adopt a modeling approach is still strong. Despite encouraging attempts to explore new transdisciplinary perspectives (see for instance the recent branching out of the Society for Anthropological Sciences<sup>4</sup> from the American Anthropological Association), computer-assisted modeling is nevertheless widely regarded as excessively simplistic. Multi-agent simulations are particularly exposed to this allegation owing to the extensive adoption of Axelrod’s (1997) “KISS principle” (Keep It Simple, Stupid) in the modeling community. The advice to build models around a small set of pre-defined rules describing agent behavior is deemed incompatible with the declared goal of detecting social complexity. Furthermore, it bears little or no legitimacy to the eyes of

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<sup>4</sup> <http://anthrosciences.org/>

researchers used to explore the subtleties and the details of human behavior in specific social settings. The accusations of reductionism and of hyper-simplification lie in wait.

Qualitatively-informed ABM still needs to attain its standard of excellence, and this cannot ultimately be achieved without overcoming a certain mutual skepticism between modelers and qualitative researchers. The need for transdisciplinarity does not only rely in the preparation of material conditions for research (training, funding, curricula, etc.). It also relies on improved communication between researchers coming from different scientific backgrounds, as a mean to create increased opportunities for mutual enrichment.

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