INTERNATIONAL REVIEW OF SOCIAL PSYCHOLOGY

Eberlen, J., et al (2017). Simulate this! An Introduction to Agent-Based Models and their Power to Improve your Research Practice. *International Review of Social Psychology*, 30(1), 149–160, DOI: https://doi.org/10.5334/irsp.115

RESEARCH ARTICLE

Simulate this! An Introduction to Agent-Based Models and their Power to Improve your Research Practice

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The method of agent-based modeling is rarely used in social psychology, but has the potential to complement and improve traditional research practices. An agent-based model (ABM) consists of a number of virtual individuals – the "agents" – interacting in an artificial, experimenter-controlled environment. In this article, we discuss several characteristics of ABMs that could prove particularly useful with respect to recent recommendations aimed at countering issues related to the current "replication crisis". We address the potential synergies between planning and implementing an ABM on the one hand, and the endeavor of pre-registration on the other. We introduce ABMs as tools for both the generation and the improvement of theory, testing of hypotheses, and for extending traditional experimental approaches by facilitating the investigation of social processes from the intra-individual all the way up to the societal level. We describe examples of ABMs in social psychology, including a detailed description of the CollAct model of social learning. Finally, limitations and drawbacks of agent-based modeling are discussed. In annex 1 and 2, we provide literature and tool recommendations for getting started with an ABM.

Keywords: Social Psychology; Agent-Based Models; Computational Social Sciences; Replication Crisis; Methodology

Introduction

In recent years, more and more phenomena that were believed to be established results in social psychology have been found to disappear when the original experiments were replicated (e.g. Klein et al., 2014; Open Science Collaboration, 2015). Recommendations to prevent replication failures are plentiful and include building better theoretical foundations, pre-registering studies before starting the data collection, as well as encouragements to use different statistical methods. We believe that agent-based modeling can be a helpful tool for social psychologists if used as a complement to traditional research methods. Notably, researchers can profit from synergies between the development of an agent-based model (ABM) and several of the recommendations made in the light of what has become known as the "replication crisis". Therefore, we introduce agent-based modeling and its uses for social psychology in the current quest for improved research practices, and provide tools and knowledge necessary to start creating ABMs yourself.

Agent-based modeling is part of a larger, powerful family of computational modeling techniques that are used to better understand and explore social phenomena. These methods are designed to explore not only the end state of social and cognitive processes, but also the dynamics of the process itself (Richardson, Dale & Marsh, 2014). Agent-based modeling consists of creating an artificial population of agents that can represent individuals, organizations, or several groups within a society. Agents can display considerable variability, both by belonging to different groups with inherently different traits, and by possessing traits or displaying behaviors to different degrees (Epstein & Axtell, 1996). In an ABM, agents interact with their environment, including other agents, but also (simulated) resources and physical structures. These interaction processes take time into account, and thus can explicitly simulate dynamical processes. Agent-based modeling allows for the development of testable theories and systematic experimentation through simulation (Conte & Paolucci, 2014). An exploration of the artificial experimental setup, using different rules and parameters, allows modelers to define a set of rules or theoretical assumptions about the agent's behavior which are sufficient to reproduce phenomena of interest at the level of the artificial population.

While there are others who argued for the use of ABMs in social psychology before (Smaldino, 2016; Smaldino, Calanchini & Picket, 2015; Smith & Beasley, 2015; Hughes, Clegg, Robinson, & Crowder, 2012; Smith & Conrey,

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2007; Jackson, Rand, Lewis, Norton & Gray, 2017), the use of ABMs in social psychology is still rare. However, we believe that the current climate of renewal, including the aforementioned new methodological recommendations to improve replicability and a lowered threshold for the use of computer programming, offers ideal conditions for the integration of agent-based modeling into the canvas of research methods in social psychology. We suspect the biggest remaining hurdle to use ABMs as a complementary tool in social psychology is the lack of knowledge about the many advantages and the synergic effects with the quest to improve current research practices. Therefore, we first discuss what social psychologists can gain by using ABMs. Specifically, we discuss how ABMs are helpful for theory development, planning and executing real-life experiments, and how they can provide support in the endeavor of pre-registration. In addition to these advantages, having created an ABM can also facilitate scientific communication as it demands a clear and detailed understanding of the hypothesis, and it can be used as a didactical tool to illustrate the key aspects of your research. These characteristics provide the researcher with ample opportunity to practice open science. Finally, compared with traditional methods, ABMs can facilitate the simultaneous exploration of interactions between intra-, interpersonal, and intergroup phenomena.

To illustrate the use of ABMs for social psychology, we take an in-depth view at a model of social learning through group interaction, the CollAct model (Scholz et al., 2014; Scholz 2016), and describe several other examples of ABMs relevant to social psychologists. Following the presentation of CollAct, we discuss the limitations and drawbacks of agent-based modeling.

To ease the way into getting started with agent-based modeling, we provide a selection of literature, tools and pointers in the annex. This annex is tailored specifically to the needs and background of social psychologists, so you can make use of skills you might already possess.

The Role of ABMs in Current Social Psychology

The way classic methods and practices of experimental design, data collection and data analysis were used over decades in social psychology are increasingly challenged and criticized (cf. Banks, Rogelberg, Woznyj, Landis & Rupp, 2016; Simmons, Nelson & Simonsohn, 2011). Accounts of failures to replicate prominent studies have made it into mainstream media, as was recently the case with research on the "power pose" effect, where assuming an open assertive posture was believed to lead to changes in hormone levels, higher propensity to risk taking, and feeling more powerful (Carney, Cuddy & Yap, 2010; media coverage: Friedman, 2016; Gelman, Fung & Miller, 2016). Due to such replication failures, methods and practices that were considered common standard before are now questioned and actively discouraged (e.g. unjustified and small sample sizes, presenting exploratory analyses as confirmatory), and methodological alternatives as well as improvements are proposed (Asendorpf et al., 2013; Nosek & Lakens, 2014; Pashler & Wagenmakers, 2012).

Currently, several projects are dedicated to rebuilding the foundation of social psychology. Direct replications of studies originally conducted before the onset of what some call a "revolution" (Spellman, 2015) aim at re-establishing a common ground for our discipline (Klein et al., 2014). The wealth of propositions to improve the quality of our research, sparked by this "crisis of confidence" (Pashler & Wagenmakers, 2012), can be interpreted as an encouraging sign. Indeed, suggestions for improvement concern all steps of the scientific process, from the theoretical foundation and formulation of the hypothesis (Klein, 2014) to experimental design, pre-registration of intended studies (Nosek & Lakens, 2014), data collection, and the analysis of the obtained data (Funder et al., 2014). An additional prominent recommendation is to practice open science, making the entire research process publicly accessible, providing detailed descriptions of the experimental setup, and letting everybody access the obtained data, along with data analysis scripts (Nosek, Spies & Motyl, 2012). Proponents of these recommendations hope that facilitating communication about, and understanding of, experimental research will lead to an increase of its quality (Nosek, Spies & Motyl, 2012). In the following sections, we argue that the proposed measures to combat questionable research practices (Banks et al., 2016) are partly overlapping with the tasks required in the early stages of computational modeling, turning ABMs into a useful complement to current social psychology research methods.

What Is an Agent-Based Model?

An agent-based model is a way of conducting virtual experiments consisting of computer simulations. At the core of every ABM are the agents which can be defined as "[…] a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives." (Wooldridge, 1999, p. 29, adapted from Wooldridge & Jennings, 1995). Agents are implemented as part of the source code of a computer program. During a simulation run, agents act autonomously according to rules that have been defined when programming the model. They can sense the environment and interact with it, as well as with other agents, according to rules implemented by the modeler. Agents' actions have consequences, thereby updating the current state of the whole system for the next set of actions.

Besides the concept of individual agents, ABMs are all about interactions. These interactions are based on the behavior rules and can lead to a phenomenon called "emergence", a behavior or structure on a higher level (e.g. the formation of a new norm) which cannot be directly reduced to actions on the lower level (few individuals behaving in a specific way). Instead, emergence is the aggregate result of the behaviors of a large number of individuals at the lowest (micro/individual) level. Emergent phenomena are not "built in" but originate from the simulated interactions between smaller entities, the agents. In this way, behaviors or patterns can be "grown" (Epstein & Axtell, 1996) from defined interactions at the micro level. Emergence is not specific to ABMs but is observed in the real world as well (e.g. in the formation of a norm or the creation of an ant trail). By having the possibility and need to define agents' behaviors, ABMs provide a means to integrate knowledge that is currently splintered across social psychology and relate emergent patterns that exist on an aggregate level to the individual level, at which behaviors arise.

Agent-Based Models and Pre-Registrations

A prominent measure amongst the recommendations aimed at improving the scientific process is the relatively new practice of *pre-registration* (e.g. van't Veer & Giner-Sorolla, 2016; Nosek & Lakens, 2014). Despite its young age – at least in psychology – there are already journals who either pledge to give pre-registered studies preferential treatment (Chambers, Forstmann & Pruszy, 2017) or even dedicate their space entirely to registered reports, such as the journal *Comprehensive Results in Social Psychology*. Pre-registration means that a study will have to go through the review process and obtain approval before the data is even collected, based on the quality of the hypothesis and experimental design. Submitting a pre-registration entails writing a detailed outline of the planned experiment, following a blueprint such as the ones provided by aspredicted.org (n.d.) and by van't Veer and Giner-Sorolla (2016). Such a comprehensive and concrete representation of the theoretical foundation of the planned experiment is in essence the same as the first stage in the creation of an ABM. To create an ABM, every feature or behavior that will be included in the model needs to be explicitly stated and formalized. This is necessary not only because there is a protocol, or a best-practice way to go about, but for the implementation of the model itself.

The process of specifying all components of a model helps to limit hypotheses to those that are explicitly integrated into the model: what is not there cannot be taken into account, as it will have no influence on the model output. Provided the model itself is already in an advanced stage, gaps in the theory become obvious, that is, when parts needed to make the model run are missing, such as specific interaction rules. This procedure is extremely helpful to avoid gaps that might otherwise invite researchers to form *a posteriori* hypotheses, and meaningfully explain (or explain away) unexpected experimental results.

In short, while designing an ABM, a researcher necessarily creates an elaborate pre-registration template, and by implementing it, she puts the experimental design to its first test. On the other hand, if a psychologist wants to employ an ABM, having a well-written pre-registration can be of immense help for setting it up.

While not all modelers agree that an official protocol is necessary to unify the way in which these details are reported (e.g. Smaldino, 2016), there are protocols used more and more frequently for communicating models, such as the ODD and ODD+D (Grimm et al., 2006, 2010; Müller et al., 2013) that help structure and communicate implicit knowledge.

In addition, the elaboration of a plan for an ABM and creating the model itself can improve the theoretical background of the proposed experiment. This can then lead to an increase in the quality of the experimental design as the researcher has a precise idea of what she is actually investigating.

Theory Building through Agent-Based Models

The suggestion to build an experiment on a solid theoretical framework (Klein, 2014; Świątkowski & Dompnier, 2017) is the one that most readily supports the use of ABMs. Theories serve as an anchoring tool for the research process. A well-elaborated theory informs the experimental hypothesis, as even with different experimental setups, the crucial components to be tested can be identified. This does not necessary mean that the theory will be confirmed. However, without an underlying theory, a study can explore possible relations between different variables, but the researcher won't be able to draw confirmatory conclusions as there is no theoretical frame of reference against which the data obtained can be tested. Testing an intriguing, counterintuitive hypothesis can be successful, but it might only be successful because of the specific dataset obtained and not because there is actually an underlying general phenomenon (Klein, 2014). In addition, without a well-elaborated theory, data can be explored in many different ways until the researcher obtains an interesting result. It is only in the second step that she will explain the reasoning behind the results, filling in the gaps of the initial theory.

Agent-based modeling is a method that lends itself extremely well to the elaboration of theories: As stated above, in order to create an ABM, it is vital to define the specific components of the model before the beginning of the actual modeling process. This forces the researcher to think thoroughly about the purpose of the model in the first place. Agents' knowledge and behavior must be set and formalized in a conceptual model, whose level of detail allows for an implementation in a programming language (cf. Salamon, 2011). Thereby, it becomes obvious if a necessary portion of information is missing. A typical example for this are rules for dynamic processes and interaction, which are missing in many theories, such as in the Theory of Planned Behavior (Ajzen, 1991). Creating an ABM based on the theoretical reasoning of the researcher can be useful to avoid the auxiliary assumptions which Świątkowski and Dompnier argue could be a culprit in the current situation in social psychology (2017). Often, additional (social) influences are not explicitly taken into account in the statistical analyses. ABMs allow experimenting without additional influences, or including assumed social components explicitly, thereby testing their importance in the initial theoretical assumptions. Once the model is implemented, it can be used to test different parameter configurations. This can be useful to test the robustness of a theory or phenomenon investigated: minor parameter variations or an increase in the number of agents should not lead to a major change in the results obtained with the model. Thereby, obtaining replicable results from the experimental setup built by the researcher should not depend solely on recreating original experimental conditions down to the last detail. The reader interested in learning more about theory building through agent-based modeling will find some excellent and detailed discussions in Smaldino (2016), Smaldino et al. (2015), Hughes, Clegg, Robinson and Crowder (2012), as well as Smith and Conrey (2007).

Agent-Based Modeling Can Help to Improve Scientific Communication

Another aspect frequently evoked by proponents of better research practices is openness: making material necessary for the experiment, as well as the data obtained, publicly available (Nosek, Spies & Motyl, 2012). While not true for all agent-based modelers, it is increasingly common practice to publish the model, either directly in the form of its code or online with a user interface. Personal websites, blogs, but also collaborative software repositories such as GitHub (github.com, n.d.), and the numerous model libraries such as the CoMSES library found on openABM (CoMSES Computational Model Library, n.d.) make publishing models easy. Sharing ABMs this way allows other researchers and even lay-people possessing the sufficient skills to try out the model for themselves (see, as an example, Gray et al., 2014). Interactive user interfaces especially benefit scientific communication: Seeing the implemented theory in action can be a great help in understanding it in more depth, and it does not require the user to possess programming skills. Anybody can then actively explore the implementation of the experimental hypothesis by manipulating the variables, exploring what behavior has an impact on specific agents, on subgroups or on the whole population, and whether new phenomena do emerge with different configurations. Proceeding this way, not only can the data be shared, but the whole experiment can be reproduced by others.

Linking Different Levels of Analysis

Agent-based modeling is an excellent tool to investigate social phenomena at different levels, from the personal to the societal. Experiments in social psychology have to navigate between an experimental setup that mimics real-world situations at the risk of complicating later data analysis, and an over-controlled environment trying to eliminate all potentially interfering variables. In ABMs, we can create the experimental environment containing the exact amount of detail needed. There are no particular limitations to the number and nature of details that can be included in an ABM, except that they have to be computable – be it deterministically or stochastically. However, a strong bias towards simplicity should be adopted, as overly complicated models are more difficult to analyze, and the number of model parameters can be prohibitive due to the dimensionality of the space of possible parameter settings, which can become too large to be searched efficiently. We discuss this aspect of agent-based modeling in more detail in the section "Limitations and Drawbacks of ABMs".

The freedom of choice when designing ABMs includes different levels of aggregation. Doise (1982) provides one possible description of such levels. He evokes them as the intra-individual (cognitive level), the inter-individual (situational level, specific to interactions between people or between individuals and a precise situation), the level relative to an individual's position in society, and finally the level of ideologies, general ethical reference frames, or beliefs a society develops. When conducting an experiment in social psychology, the researcher can strive to manipulate and observe variables on different levels of analysis. However, it remains difficult to observe and explore in an experimental setting, for example, the circular influence of a change in individual behavior, on the individual's neighbors, which then influences a larger group or "society", which then ripples down again to the intra-individual level. The advent of social media data provides some support for investigating the interaction of the group level with individual phenomena in the real world. Nonetheless, disentangling different levels of analysis in this context holds restrictions as well, such as the lack of knowledge about intra-individual decision processes. This can again limit the possibility of investigating links between emergent, societal-level phenomena caused by individual or group-level behaviors.

Agent-based models, however, can provide us with insights on all of these levels. We can, for example, implement certain traits, preferences or behaviors within agents, as rules of interaction with other agents and the modeled environment. Subsequently, we might be able to observe the emergence of phenomena that are situated at the level of the society as a whole. A very simple, yet effective example of such a model is Schelling's model of residential segregation (1978), where individual preferences to live close to some people who share specific characteristics lead to completely segregated neighborhoods.

Inherently, models are simplifications of reality. Even so, agent-based models provide the possibility to implement as much detail as we require. On the one hand, this allows us to render a naturally complex situation simpler, thereby disentangling different variables and their influence. On the other hand, however, we can also implement the results of a highly controlled experimental situation in a more realistic setting. An example of this could be to use data obtained through an implicit association test (IAT, Greenwald, McGhee & Schwartz, 1998) to model individual biases of our agents. Then, by running the model over several time steps, we can observe how personal biases in several individuals might lead to larger phenomena, spanning more than the intra- or even inter-individual level.

Using Agent-Based Models to Widen the Scope of Investigation

A typical problem of experiments in social psychology is the low statistical power of many experiments, constraining their capacity to detect a true effect. The two main reasons for this are small sample sizes and a small base rate occurrence of the effect investigated in the general population, provided it exists. Creating an ABM of the experimental hypothesis will not allow a researcher to continue doing underpowered laboratory or field studies. However, it can complement a well-designed, sufficiently powered study: Once a model is implemented and validated through comparison to experimental or empirical data, it is possible to increase the number of agents to a sample size that is not obtainable by traditional methods. It is then interesting to observe whether the phenomena observed with a smaller number of agents still hold for an entire population, when interactions of a larger number of agents are taken into account. This also serves as a test of whether change in the dependent measures used in the experimental setting is truly due to the experimental manipulation or hypothesized variables and not another unaccounted influence: the model contains only what the researcher implemented, so if a phenomenon is not observed in the model but only in the real-world setting, the underlying theoretical assumption are at least incomplete. Another possibility would be to introduce additional interaction structures, such as agents situated in a network. This has been done, for example, by Luhman and Rajaram in 2015 (see following section).

Another advantage of ABMs is to change interaction rules and variables to explore in which way this affects simulation results. This type of model exploration is one of the greatest strength of agent-based modeling, and can lead to the formulation of new research questions. For example, the effects of a specific variable or interaction rule can be tested in the model, and if interesting effects appear, these can be tested in follow-up real-world experiments. Additionally, starting out with an ABM implementation of the hypothesis allows testing it under ideal conditions before investing it experimentally. The researcher will then have a better understanding, given her hypothesis, of the magnitude of effect she might expect. This increases her ability to estimate whether her resources are well invested in this study.

Agent-Based Models in Social Psychology

Agent-based modeling has previously been used both by social psychologists and by modelers making use of social psychological paradigms. We use four recent examples to illustrate how ABMs have been used to explore research questions relevant for social psychologist. Then, we provide a more detailed description of the CollAct model (Scholz et al., 2014; Scholz, 2016), in order to illustrate the main principles of agent-based modeling.

Festinger's social comparison theory (SCT) has been implemented by Van Rooy, Wood, and Tran (2016). The model is based on a connectionist framework, where each agent is capable of relatively complex learning principles, as well as a dynamic network context, where agents create and loosen ties based on similarity in their attitudes. This implementation of the SCT brought new insights to both social psychologists and modelers: For psychologists, breaking down SCT into step-by-step instructions for a computer program clears up "aspects of the theory [that] are couched in ambiguous verbal descriptions" (Van Rooy, Wood & Tran, 2016). Agent-based modelers, on the other hand, have a tendency to simplify the cognitive aspect of agents, thereby reducing the (social) psychological validity of a model. Van Rooy, Wood, and Traan's model is also a good example of the integration of ABMs and a real-life experiment, where one reproduced similar results to the other.

Gray and colleagues (2014) have explored group formation in a homogeneous population, based on reciprocity and transitivity. The agents in this model initially don't belong to different groups, nor do they possess features that would justify an external classification in one group or another. Rather, the model investigated whether cooperating and defecting in the prisoner's dilemma would, over time, lead to group formation in a population where agents can form and sever ties with each other. The influence of trust, reciprocity, transitivity, and the number of agents on the formation of groups was manipulated by the researchers, and you can do the same on www.mpmlab.org/groups/. This interactive version provides a compelling additional tool to help readers understand the underlying reasoning and implications of the variables implemented in this model of group formation.

Luhmann and Rajaram's model (2015) of memory transmission in groups is an illustration of the use of agent-based modeling as a complementary tool. First, they simulated different aspects of empirically investigated phenomena of memory transmission in groups. By choosing to build their ABM based on the same experimental paradigms as the real-world experiments in the relevant literature, their model held a validation with regards to experimental data. After this corroboration of their ABM, they extended it to a higher number of agents beyond the sample sizes possible in the controlled laboratory experiments. This allowed Luhmann and Rajaram to discuss the robustness of the investigated phenomena: if the theoretical assumptions are true and the collected data generalizable, they should lead to the same outcome, whether implemented in the model or tested in a laboratory setup, and should withstand variations in sample sizes. Furthermore, using an ABM allowed them to explore new dimensions of memory transmission: agent communities had the same initial setup for individual behavior, but differed in network structure. This configuration allowed Luhmann and Rajaram to observe how memory transmission works outside of closed groups, which would have been unfeasible in a traditional experimental setting.

Finally, agent-based models have already played a role in the current debate about replicability. Namely, Smaldino and McElreath created an ABM to investigate how the quality of publication evolves in an environment that values original research over replication efforts (Smaldino & McElreath, 2016), unfortunately with discouraging results. This final example illustrates the value of creating an ABM prior to implementing a real-life experiment or intervention method: The results of the ABM suggest that low-effort science is more successful than high-quality – but also time and resource intensive – science, and replication efforts in the current form might not be sufficient to prevent future editions of the current crisis of replication. This ABM also illustrates that an agent can be a unit other than a person: Smaldino and McElreath consider that each agent as representing a lab rather than an individual researcher.

The examples of ABMs given here are by no means exhaustive: for more examples, see Jackson et al (2017), who provide a table of ABMs relevant to social psychology. To further demonstrate the creation and usefulness of an ABM, we introduce the CollAct model in more detail.

CollAct, a Model of Group Discussions

To understand the technique of agent-based modeling in more detail, we now discuss CollAct (simulating collaborative activities; Scholz, 2016; Scholz et al., 2014), an ABM of group interaction, as a more elaborate example of a model using findings of social psychology. CollAct is an explorative model, designed to help to analyze factors that influence learning and explore the social dynamics occurring in group discussions. It is built upon the idea that group interaction can foster social learning processes. These are in turn expected to enable or promote social change for sustainability (e.g. Muro & Jeffrey, 2008). To this end, CollAct models both cognitive knowledge (referring to knowledge about a topic at stake) and relational knowledge (referring to the perception of other participants and self-perception), as well as learning. Agents in CollAct discuss an abstract issue (e.g. a management plan) and try to reach a consensus. Here, consensus is defined as a general agreement that might include aspects of the discussed topic on which certain participants have doubts or disagreements, but do not communicate them. Cognitive and relational knowledge are used to interpret incoming messages and decide upon further actions (sending out a message, and if so, which message). CollAct is implemented in Repast Simphony (North et al., 2013). An executable version and an ODD description of CollAct can be downloaded here: https://www.openabm.org/model/4255/version/1/view. Please note that, in order to run this model, you need to install Repast Simphony first (see Annex 2).

In CollAct, agents discuss with each other in a virtual room called *discussion* by exchanging messages. Messages contain information about the speaker, the content, which is an aspect of the issue at stake, and whether or not this content should be included in the consensus. Thereby, the discussion takes place in a turn-taking manner, and all agents hear all messages. If more than one agent wants to speak, a random process decides which agent is first. Furthermore, a protocol saves the recent messages and frequency of content-related messages, to assure path-dependency in the discussion. Content that a sufficient number of messages advocated for is included in the consensus. We focus our description on the class *participant*, which implements the agents. Agents in CollAct have mental models, referring to personal internal representations of the surrounding world that determine how one observes the environment (Johnson-Laird, 1983; Jones, Ross, Lynam, Perez & Leitch, 2011; Kolkman, 2005; Norman, 1983). Agents use the knowledge in their mental models to evaluate the perception of the environment, i.e., to interpret the incoming messages. Every agent has a mental model consisting of two "sub-models": the *substantive model* (knowledge about the topic at hand) and the *relational model* (knowledge about other actors and self-perception). Individual characteristics are grasped through different knowledge in the mental models (about the discussed topic, other participants, and self-perception). The relational models of agents are modeled as real numbers between 0 and 1. Substantive models represent the importance that an agent attributes to a set of aspects of the issue currently discussed, which can be communicated in a message. Substantive models are implemented as an *array*. An array is a data type you can imagine as a box with different compartments, labeled by increasing numbers. Scholz et al. (2014) linked every compartment to a specific aspect (e.g., compartment 4 refers to aspect xy). A "1" implies an agent finds this aspect important, a "0" that the agent does not find it important or does not know about it. **Figure 1** shows a representation of such a substantive model, a box with different compartments filled with 0's and 1's. Learning is simulated through change in the substantive and/or relational model of an agent. The implementation of learning was based on the findings that confrontation with new knowledge can lead to a change in concepts (Anderson, 2000), and that people develop concepts

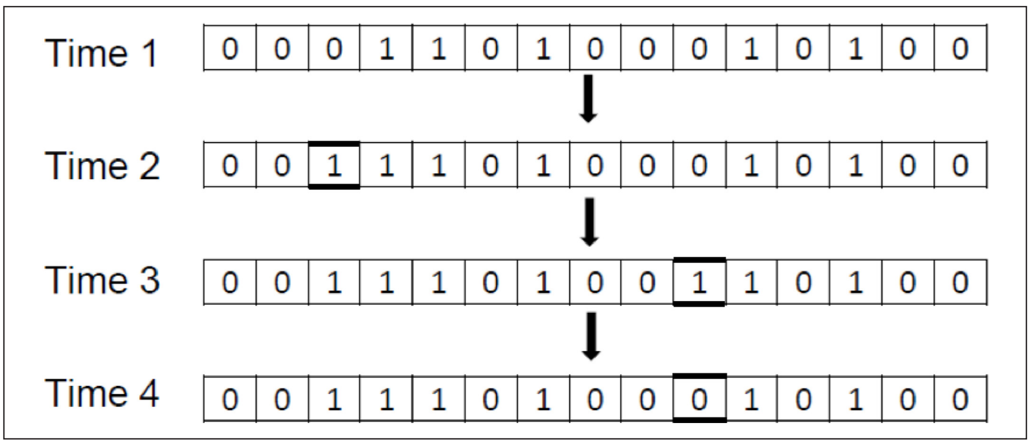

Figure 1: Example displaying how the substantive model is implemented in an array. The agent changes her substantive model three times, learning new aspects the first two times, and forgetting an aspect the third time.

quickly on little evidence and have a tendency to stick to these concepts without strong evidence in contradiction of them (Dörner, 1999). **Figure 1** shows how the substantive model of an agent may develop during the simulation run.

The emerging consensus in the simulation run is modeled by a similar array. In this way, it is easy to compare whether and to what extent individual agents' mental models and the negotiated consensus overlap in the end.

In group discussions, conformity is one major influence (cf. Baron & Kerr, 2003). To mediate and integrate effects from the relational model with the substantive model and the ongoing discussion, conformity is modeled as a cognitive bias. To this end, the Asch effect (Asch, 1951) and the halo effect (Thorndike, 1920) are integrated as thresholds in the behavior of the agents. The strength of these biases is a parameter that can be set to test different scenarios in the simulation.

The routine for whether an agent decides to speak up, and what they would say, is implemented as a decision tree comprehending stochastic influences. **Figure 2** displays the core of this decision routine. To understand how the decision tree is used, we describe one possible path along its branches: In the beginning, the agent checks whether she is interested in the content or the speaker/sender of the message. To this end, the message is first compared to the agent's own substantive and relational model. If the derived values suggest that the agent is neither interested in the content nor in the speaker, the agent decides to send out a message with a new content.

CollAct was set up stepwise, testing each model part (e.g. the discussion) for proper and reasonable dynamics and outputs. This proceeding helps to avoid implementation errors and understand the dynamics produced by the different model parts (e.g. whether and how path-dependency in the discussion works), thus facilitating model-building and understanding of the model results. To estimate the influence of different parameter values on the outcome, a sensitivity analysis was performed using the parameter sweep function from Repast Simphony. During a parameter sweep, the program performs several runs of the model with different parameter values within a range predefined by the modeler. For the final model, results were discussed with experts and compared to existing literature.

CollAct produces discussions with successive clusters of messages on the same aspects of an issue at stake, the development of a shared understanding, and the shift of roles through learning in relational models. **Figure 3** displays the output from one single run, in which different agents (speakers) "talk" about different contents.

When it comes to factors having an influence on the consensus and on the amount of learning, the important factors turn out to be group size, the level of controversy within the discussion, available knowledge, knowledge distribution, and conformity. For the influence of conformity on the consensus, results suggest that while high conformity and a low controversy in the discussion both foster a broad consensus comprehending many aspects, cognitive learning is needed to build a shared understanding and to increase the support of a consensus (overlap of the consensus with the mental models of agents). This result is intuitive. Nevertheless, in the scientific discussion on social learning in natural resources management, the need for cognitive learning

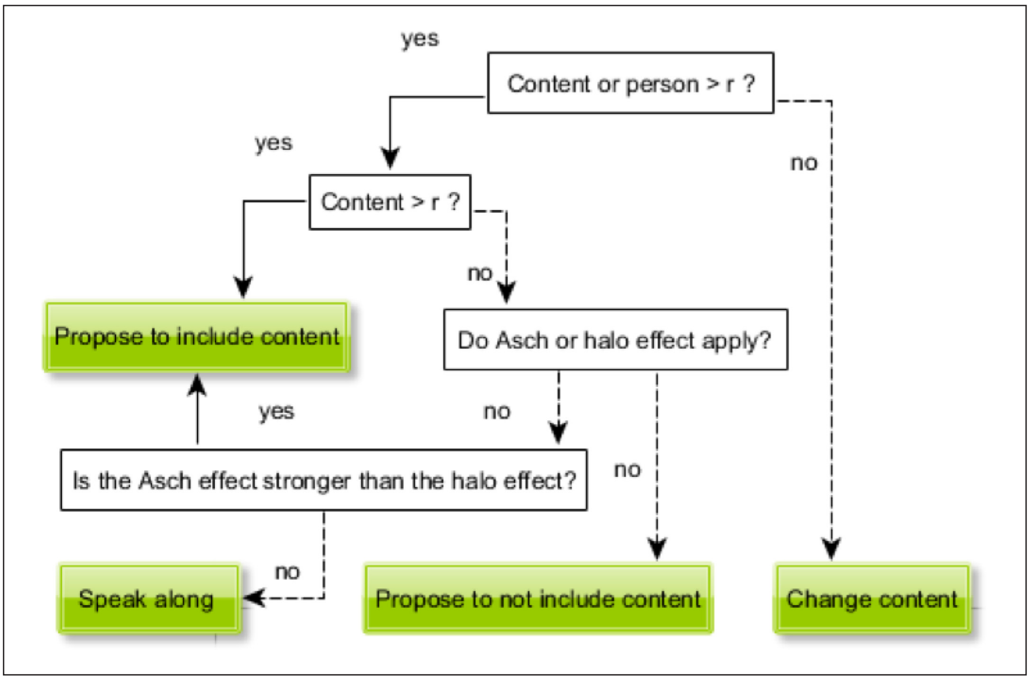

Figure 2: Agents' decision routine for choosing a message. Possible outcomes are in green boxes. r refers to a random number, while the probabilities for the Asch and the halo effect to occur are parameters that can be varied. The values for content and person are derived when the agent evaluates whether she agrees to the last message (is the content included in my substantive model?) and who the speaker was (value in relational model).

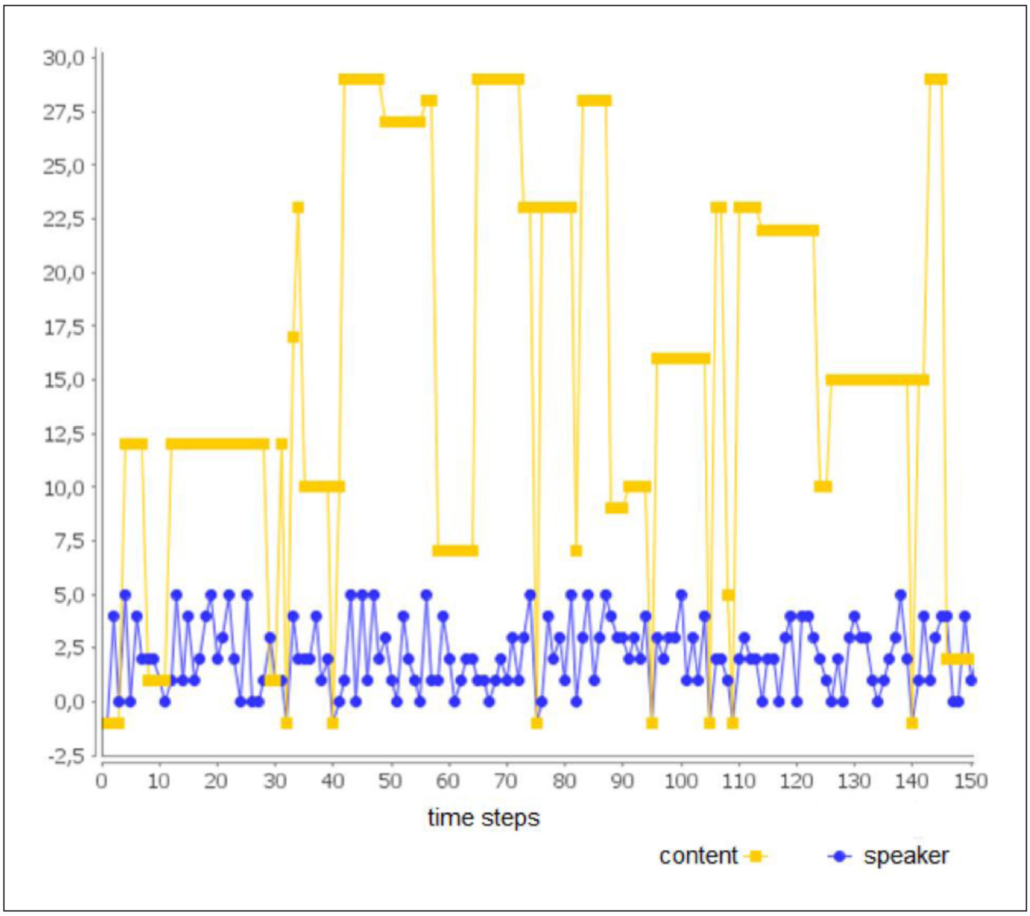

Figure 3: Output from CollAct showing successive clusters of messages on the same aspects of an issue at stake (contents 0–30, referring to a specific compartment of the substantive model of agents). Different speakers are displayed by their identification number (e.g. in time step 11, agent number 1 sends a message about content 12, followed by a discussion about this content in which all six agents send messages). A value of –1 for the speaker (blue) means that no agent is speaking at that time step.

and thus the need for higher resources (e.g. time) is often not as prominent, and only recently Beers and colleagues (2016) found that conflictual interaction might enhance learning. This demonstrates that using an ABM such as CollAct as a thinking tool can help to achieve more consistent conclusions from assumptions, including your own. Another result from CollAct is that high mutual esteem and the building of a shared understanding reinforce each other. This is due to the implementation on the micro level: first, the probability for agents to learn from each other depends upon their mutual esteem; and second, mutual esteem tends to be high in presence of a similar opinion. These two micro-level assumptions result in a reinforcing feedback between high mutual esteem and the building of a shared understanding at group level. Hence, CollAct can serve as a thinking-tool to link theoretical assumptions at the micro level to emergent outcomes at the group level, supporting the analyses of trade-offs in group interaction.

Moreover, not only the parameters, but also micro-level assumptions and input values for agents' mental models can be varied. Through a variation of micro-level assumptions (e.g. a different decision tree) different hypotheses can be tested for their ability to reproduce realistic model outputs. In this way, hypotheses can be specified, and gaps in an explanation (where no realistic behavior is observed) may become obvious. Simulating different mental model combinations can aid to specify characteristic group compositions that result in interesting outcomes in simulation experiments. Such characteristic group compositions and dynamics can then be further investigated in empirical research, and if confirmed, CollAct may serve to test intervention measures (e.g. increasing the controversy of the discussion).

Limitations and Drawbacks of Agent-Based Models

Despite the numerous benefits of agent-based modeling as a research tool, there are several challenges associated with creating ABMs. We address common difficulties such as the integration of too many features and the choice of the parameters. The results of models are often criticized for being either trivial or, on the other hand, too complex and therefore probably wrong because of their surprising results (Waldherr & Wijermans, 2013).

As we mentioned already in the section "Linking Different Levels of Analysis", selecting the adequate number of parameters, features, and behaviors to include in the model can be challenging, both on the practical and the theoretical level. In practical terms, integrating a large amount of details will make programming the model more challenging, as each model feature needs to be defined and integrated with the other model components in a meaningful way. However, even if the scientist overcomes this hurdle, a model with a large number of parameters will be of limited theoretical value. One reason for this is the so-called "curse of dimensionality": increasing the variables integrated in the model decreases the number of observations per cell. If we want to obtain meaningful statistical results, it is useful to either keep the number of variables as low as possible or increase the number of agents and runs. A different and arguably even more important aspect of the "curse of dimensionality" is that it might not be possible to interpret the model in a meaningful way if there are too many variables to take into account. As social psychologists, we are very well versed at simultaneously referring to and ignoring this limit in our work ("further investigation of V taking X, Y, and Z in addition to W, into account, is needed to clarify this question"). Creating an ABM gives us the possibility to explore further, and more complex interactions between variables, but any modeler has to be careful to avoid including more components than necessary. This is the principle of Occam's razor applied to agent-based modeling: limiting model parameters to those strictly necessary for the implementation of the hypothesis.

However, the ability to accommodate more than the necessary number of variables can also be a strength of ABMs: it allows us to explore which variables actually add value and to identify those that are critical to the implemented theory. By stepwise increasing or reducing model complexity, ABMs can help us to define the limits of a theory, hypothesis, or experimental finding more clearly. Once these limits are identified, the researcher can make an informed decision as to whether the hypothesis is suited to be tested in a traditional, real-world experiment.

Regardless of the number of components implemented, their selection, such as the number and type of agent, rules, and updating processes. can also be subject to criticism. This problem of model specification is not unique to ABMs: in other types of models, e.g. equation-based models, details that have to be specified in ABMs are aggregated in functions and parameters, and thus, uncertain design choices are "hidden" in the model. In an ABM, they can be made explicit. This leads to a better understanding of the processes that the modeler set out to investigate in the first place, as well as more transparency in comparison to equation-based models or experimental designs where the details of the theoretical foundations can be glossed over (Wilensky & Rand, 2015, p. 36). At the same time, the freedom and necessity to define all model elements is the largest challenge when designing an ABM. It is possible to leave in free parameters that cannot be empirically measured to design an executable model. Such parameters can be varied to explore the model behavior, and also, they can be calibrated to empirical data of the system which is modeled. This bears the danger of "overfitting", or the process of adapting values for parameters so precisely that they describe one specific sample of data instead of a more general phenomenon.

What differentiates the processes of selecting features and calibrating parameters from the questionable research practices of adapting hypotheses after the collection of data, or leaving out collected variables and data points in order to make a scientific contribution more interesting for publication, lies in the nature of the ABM as a closed system. Of course, the modeler can simply refrain from reporting certain aspects of her model, but she cannot leave them out of her implementation. However, we have to stress that, ultimately, there is no substitute for good scientific conduct and research ethics.

Another pitfall of ABMs is to take the implemented procedure based on the theoretical assumptions and results model as the mirror image of the same processes and observations in the real world. While the model can serve as a "proof of concept", it cannot be conclusive evidence by itself. Rather, as stressed before, it is a valuable addition to existing research methods and can help alleviate difficulties researchers encounter when using empirical methods alone, as described in the first part of this article.

Quite often, the results obtained from an ABM seem obvious. This is similar to hindsight bias in classic experiments. There are two scenarios: First, by creating an ABM, we have realized that the results are actually trivial – in this case, the ABM has fulfilled its use as a thinking tool. Second, the possibly unexpected result seems suddenly more plausible than the initially predicted outcome. Differing from a real-world experiment, here, we have the support of the implemented ABM that the surprising result is actually the outcome of the dynamics programmed into the model.

Finally, the main obstacle to overcome is often that of learning to build an ABM, which can be quite challenging and involve a steep learning curve. It implies acquiring both new theoretical knowledge about ABMs and new practical skills for programming the model. We provide suggestions for accessible literature on agent-based modeling in annex 1. These will help you to familiarize with the necessary knowledge to translate a verbal theory or hypothesis into an ABM. Regarding the use of programming languages, many scientists might already be more familiar with these than they think: languages like R Development Core Team, 2008 and Python Software foundation, n.d. are more and more common instruments for statistical analyses and programming experiments. To facilitate the choice between the different tools available, annex 2 contains a number of tools, packages and software recommendations for the creation of ABMs.

Conclusion

Despite the previous appeals for the use of agent-based modeling, it is not a commonly used method in social psychology yet. We believe that the time for ABMs has come, not least because of the need for improvement of our current scientific methods. Pre-registrations, improving the theoretical foundation of our research, and other recommendations to combat the replication crisis can create synergies with, or directly profit from, the creation of ABMs. We assume the main reason for the limited use of ABMs in social psychology is merely that this technique is not (yet) widely known, and those who have heard about ABMs are intimidated by the challenging process of getting acquainted with the technique.

The wider use of computer programming in psychology may lower the hurdle to get involved with creating ABMs. The number of researchers using some form of programming, be it for data analysis, designing experiments, or any other aim such as producing a website, has grown in the last decade. Moreover, the usability of the available software libraries has improved. Therefore, the creation of a computer-based simulation should not seem as intimidating, as it does not have such a steep learning curve as just a few years back.

Still, integrating a new methodology into an established research routine can be time consuming. Here, again, agent-based modeling has characteristics that can facilitate the steps to a first model. Due to its use in several different disciplines, uniting researchers with different theoretical as well as methodological backgrounds, there is a large number of different tools available. In the annex, we provide a non-exhaustive list of those resources and instruments. We start with different model libraries and journals dedicated at least in part to ABMs, as sources of further examples. This is followed by recommendations of practical guidelines in the literature, online tutorials, and introductions. Then, you will find a short selection of programs and programming languages that can be used for agent-based modeling, with a focus on accessibility as well as pre-existing knowledge social psychologists might already possess. Finally, we give recommendations on where to look if you are searching for more experienced modelers to initiate collaborations, as well as university departments who might organize classes on agent-based modeling.

Agent-based modeling as a complementary research method has a high potential to facilitate and improve research practice of social-psychologists. Particularly in the light of the current replication crisis, and with increasing computer literacy, we believe that this is the right point in time for social psychologists to start using ABMs.

Additional Files

The additional files for this article can be found as follows:

- **Annexe 1.** How to Get Started with Agent-Based Modeling: Introductory Literature, Model Libraries and Tutorials. DOI: https://doi.org/10.5334/irsp.115.s1
- **Annexe 2.** Software and Languages for the Creation and Exploration of Agent-Based Models. DOI: https://doi.org/10.5334/irsp.115.s2

Competing Interests

The authors have no competing interests to declare.

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How to cite this article: Eberlen, J., Scholz, G. and Gagliolo, M. (2017). Simulate this! An Introduction to Agent-Based Models and their Power to Improve your Research Practice. *International Review of Social Psychology*, 30(1), 149–160, DOI: https://doi.org/10.5334/irsp.115

Published: 03 July 2017