University of Groningen

Introduction of the special issue

Jager, Wander; Ernst, Andreas

Published in:
Journal of Environmental Psychology

DOI:
[10.1016/j.jenvp.2017.07.002](https://doi.org/10.1016/j.jenvp.2017.07.002)

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Document Version
Publisher's PDF, also known as Version of record

Publication date:
2017

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Jager, W., & Ernst, A. (2017). Introduction of the special issue: "Social simulation in environmental psychology". *Journal of Environmental Psychology*, 52, 114-118.
<https://doi.org/10.1016/j.jenvp.2017.07.002>

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Introduction of the special issue “Social simulation in environmental psychology”

Smoking changed from being “normal behavior” performed everywhere to a minority behavior performed mainly outside. Critical in understanding the social dynamics of such a major shift is the notion that other people's behavior serves as a (normative and/or informative) input for one's own behavior, and that one's own behavior in turn serves as input for other people as well. This coupling often causes a strong social resistance against change (norms), but once a change is happening, non-linear cascade effects may emerge leading towards a “tipping-point” towards new behavioral practices (Nyborg et al, 2016). In this special issue we will present the method of social simulation as a scientific tool that allows for systematic experimentation with such social dynamics in large populations.

Many environmental problems share with the smoking example this coupling of individual and collective behavior. How we transport ourselves, what we think about disposing waste and how we share collective resources are examples of domains displaying strong couplings between individual behavior, the social context and the physical environment. Such couplings have implications for the stability of collective behavior. On the one hand very stable (locked-in) situations may emerge due to the strength of a social or socio-technical context. For example, your transportation behavior is most likely to be very stable over time. However, a stable behavioral system may become unstable and change - sometimes radically so by reaching a so-called tipping point - if an increasing number of people change their behavior, the smoking example being a nice illustration of such a process. Here, the coupling results in social processes that may become self-amplifying: the more people change, the stronger the social pressure on other people to change as well. Understanding the behavioral dynamics in such social-environmental domains contributes to the development of policy-strategies aimed at a sustainable society, and hence raises relevant questions for environmental psychologists.

Within the field of environmental psychology an abundance of laboratory experiments and field studies have been conducted unravelling the social and individual motives and perceptions for man's behavior in social-environmental contexts. A large set of methods (Gifford, 2016), among them statistical methods, in particular general linear modelling, has contributed to our understanding, and often the prediction of behavior. Whereas in relative stable situations this methodology performs well, in situations where for example disruptive innovations enter society, and people increasingly share information and norms are changing, a methodology is needed that is capable of addressing the often nonlinear longer-term dynamics resulting from this coupling of individual and societal behavior. A systems understanding, considering multiple and changing behavioral drivers, is needed to study the social-

environmental dynamics emerging over time. Laboratory studies do not allow for studying large groups of people over prolonged periods of time. Field studies are more suitable, however, because of the openness of the experimental situation (social network) there is no control over the social influences, and hence the possibility of systematic experimentation in controlled conditions is limited at least. Especially in situations with a lot of uncertainties about future behavior, e.g. because of developing social norms (e.g., on food), or future technology (e.g. robotics, AI), field experiments lack experimental power. Moreover, conducting large scale field experiments is very costly, and may raise ethical concerns.

1. Social simulation in environmental psychology

Social simulation (also referred to as agent based modelling) has been one of the most interesting methodological developments of the last decades for the behavioral sciences. Starting from computer science, artificial intelligence, and complexity science, it has matured to deal with genuinely social science aspects. Conducting experiments on artificial populations, social simulation provides a computational methodology to systematically explore how collective behavior arises from interactions between many individuals (emergence), and how in turn the behavior of a collective influences individual behavior (downward causation). The seminal work of Nobel laureate Thomas Schelling (1971) for example demonstrated that in an ethnically mixed society, where the individuals prefer merely not to be in a minority in their local neighborhood, a completely segregated society emerges as a result. Schelling's social computational model was one of the first where individual decision making, in this case the choice to stay or to move away from a location, was made dependent on the behavior of the other individuals, in this case neighbors staying or moving away. This methodology opened a new perspective on studying social dynamic phenomena in coupled systems.

Since those early years, an impressive increase can be seen in studies using social simulation as a methodological tool. The rise of computing power and the development of more accessible platforms for developing social simulation models have contributed to the rise in popularity of this method in a number of scientific disciplines. Especially in the field of environmental psychology, where many research questions deal with behavior change of large groups of people over prolonged periods of time, this method of social simulation seems to be a valuable addition to the methodological toolkit of researchers. However, within the discipline of psychology there has been only very limited attention for this computational tool. Whereas for example the Journal of Artificial Societies and Social Simulation (JASSS) is referencing a lot to social scientific

articles, a citation analysis showed that very few articles in social science refer to JASSS (see e.g. Squazzoni & Casnici, 2013; Hauke, Lorscheid, & Meyer, 2017). Whereas JASSS typically focusses at social science related topics, the impact is higher in computer sciences, physics and ecology, fields where computational modelling has been embraced as a method much earlier. One of the key reasons for this “blind spot” in the social sciences for social simulation as a method is its focus on statistical methods, whereas the attention in both education and research for computational modelling and programming is neglected (see e.g. Castellani, 2014). Also within the field of economics, where often comparable coupled systems are being studied, the need for using computational methods (agent based modelling) has been advocated (e.g., Farmer, 2016), and the field of artificial economics (econophysics) is evolving rapidly (e.g., Wall & Leitner, 2014).

One of the main challenges in using social simulation as a methodology is making the psychological theories explicit in computational terms, thus translating theoretical notions into algorithms that can be coded into the behavioral rules of a simulated agent (Ernst, 2010). Many existing theories in the social sciences are based on correlational relations, and do not offer causal descriptions of the mechanisms at a level that allow for a straightforward translation into computational terms (e.g., Schlüter et al., 2017). Also many theories address certain aspects of human behavior and decision making, whereas in social simulation it is needed to “close the loop” between behavioral drivers, decision processes, actual behavior, and the (aggregated) consequences of behavior as drivers in a next cycle (Schlüter et al., 2017). The papers presented in this special issue address this challenge of making psychological theories explicit. In the field of environmental psychology, the challenge translates into the following more specific points (Ernst, 2010):

- (1) *Explicitly consider human behavior as an ongoing process creating and embedded in feedback loops.* Human behavior is a constant flow of actions and reactions that cannot be adequately represented by a static snapshot. A process view, like in the natural sciences, helps capture the role of feedback loops, e.g. in social interaction, or feedback from physical entities like the natural environment. Many processes related to relevant environmental behavior deal with social influence, attitude change, and behavior change and innovation diffusion. Critical is that behavior change of one person at time A shapes a new condition for another person at time B, et cetera. Typically, these effects are thus temporally dependent on each other, and because there often is a strong influence (like normative and informative feedback between people), it is relevant to study how such processes evolve over time. These cascade effects often cause complexities in social systems that give rise to emergent phenomena or behavioral transitions/tipping points that become visible on the societal level – just like the smoking example. Social simulation explicitly deals with dynamics over time. It is capable of exploring how theoretically and empirically grounded psychological assumptions about individual behavior translate in such dynamical processes of change.
- (2) *Explicitly represent the processes of decision making.* Psychology deals with perception, attitudes, learning, habits, or social interaction, that all precede overt behavior. These covert concepts play – together with the interaction with the physical environment – a central role in explaining and predicting environmental behavior. Social simulation builds on these psychological concepts and empirical data about

human decision making. What is more, it exploits the computational capabilities to generate simulated behavior on psychological grounds. Social simulation is thus able to serve as a running, generative theory. This stands in contrast with data aggregation (like statistics), which in turn can be used to compare experimental data with data that has been generated by a social simulation model.

- (3) *Explicitly represent social interaction.* Environmental behavior is profoundly embedded in social interaction. Social simulation is suitable to model even larger heterogeneous populations by applying psychological theory, specifically, social psychological and micro sociological theories, and empirical data to each of the individual members of such an artificial population. Many processes of behavioral change, e.g. the adoption of new environmental technology, traveling behavior, waste management, involve the behavior of large populations of different people. Especially from a social influence point of view it is important to realize that people differ concerning expertise, motivation, social susceptibility and convincing power, and that they can have rather different positions in their respective personal networks. Social simulation allows for capturing such properties, thus exploring how processes of change are influenced, or can be stimulated by typical actors with typical properties in certain network positions. It presents a methodology that allows for translating small scale experimental findings into larger scale simulations of social systems that interact with a controlled environment over prolonged periods of time. It can thus also be regarded as an elegant method to bridge the micro-macro gap: The simulation produces behavior and behavioral consequences in the simulated environment that can be analyzed on an individual, but also on the societal level that emerges from the aggregated individual decisions and actions.
- (4) *Explicitly represent the interactions with the physical world.* It is an essential feature of environmental psychology to see human behavior as embedded in the natural, physical environment, together with its immediate or long-term consequences. The feedback from the actions may (or may not) be used to learn from and to adapt future behavior. The introduction of the physical environment into psychological theorizing also often entails differences stemming from geographical location (like e.g. upstream or downstream positions at an irrigation channel). The social part of a simulation can be – in a natural way – embedded in the simulation of the physical or biological environment. A wide range of the richness of such a model of the environment is possible. It ranges from a simple, sketchy representation of the most essential characteristics to a detailed, e.g. hydrological model, depending on what is needed for the social simulation. The simulation (being dynamic in nature) allows for speaking the same formal computational language in targeting issues that are essentially interdisciplinary. Thus it becomes possible simulating to which extent behavioral dynamics are affecting the environmental dynamics, and the other way around. Models that integrate behavioral and environmental dynamics also allow for directly linking environmental impacts to behavioral change. This shared computational language is in our view an important step in addressing environmental issues in an interdisciplinary way (Ernst, 2014; Schlüter et al., 2017). Along that reasoning, the current special issue presents a number of papers where a connection is made between the behavior of the agents and

environmental impacts. However, they are not full socio-ecological models in the sense that social simulation models are coupled to natural scientific models. We can observe that in the field of climate science, ecosystems management, ecological economics, or planning an increased demand exists for including a well-founded representation of human behavior in their models. There is a call for more psychological realism in the existing models, adding to or even replacing the current rational actor or ad-hoc approaches being predominantly used. This leads to an increase in the development of models integrating natural systems with human behavior, as fostered e.g. by organizations such as SESYNC, that is supporting interdisciplinary research directed at the interface of human and ecological systems (<https://www.sesync.org>).

2. Methodological aspects

Social simulation in environmental psychology can, above all, serve as a method to develop, specify, and test psychological theories. We see social simulation as a complementary method to classical psychological research methods. In recent years, important progress has been made in particular with the use of behavioral theory in agent based models, and the parameterization of agents using data have contributed to the maturation of the methodology (Smajgl & Barreteau, 2014). This grounding in empirical research/data results in specific research questions for field or lab experiments. How to validate social simulation models is indeed a key issue. While there is a great advantage in the degrees of freedom the model formulation allows, this formalization should be evidence-based by careful grounding the model in data and/or psychological theory. The data needed however often differ from what has been gathered up to now in psychological research. A major step to be taken by environmental psychologists using social simulation is the formalization of behavioral rules in the simulated agents. Whereas there is an abundance of literature on human behavior in environmental contexts, translating this into a set of theoretically valid and empirically parameterized behavioral rules for simulated agents is a demanding task, often underdetermined by existing models and insufficiently supported with actual data.

Whereas many multiple-regression models are available describing the relative effect of different determinants on behavior, these models do not allow for a direct implementation in social simulation models. First, a correlation does not describe the causal mechanism responsible for the effect. In social simulation models we use algorithms that capture the causal mechanisms of behavior. Second, multiple-regression models are based on the statistical analysis of behavior of a sample of people. As such they are less suitable to address the heterogeneity in a sample of people, and additional data is needed about inter-individual differences. For example, social susceptibility may vary considerably between people, and this is relevant in identifying which person (non-conformist or anti-conformist) is most likely to change behavior first in a social setting. Finally, multiple-regression based models are generally cross-sectional by nature, and are not “closing the loop” in the sense that behavior is considered as input and output in studying behavioral dynamics. This would require developmental longitudinal data of influences in (spatial) social networks, which nowadays becomes easier to collect using social media data. The modeler is thus confronted with questions such as “What theory(ies) to use in a targeted simulation model”, “How to translate conceptual theoretical descriptions into computational causal

models” and “How to parameterize a simulated population using empirical data?” (Smajgl & Barreteau, 2014).

Models may simplify reality indeed, and sometime drastically so. On the other hand, they are pitiless in pointing out their own weaknesses (stemming from the underlying theory or from the implementation of the model) and help work on them in a fruitful way. An empirical validation of a model will in most cases not only encompass the observable behavioral output but also the underlying elements and core processes. The validation of a social simulation model will be attentive to the running simulation reconstructing the empirically observed behavioral results. This can be done either by grounding the model in assumptions about individual behavior and testing it against empirical data of the overall (societal) effects, or to cross-validate it against a different set of data relating to the same level, individual or societal. Iterating the loop of modelling and empirical work makes social simulation a very rigorous method of theory testing. By implementing theories in a formal dynamic context, social simulation offers a test bed for the formal consistency of these theories, and may return questions on specific implementations and mechanisms to empirical and experimental research. In this way social simulation contributes to the further development and integration of psychological theory in a behavior dynamical context. However, this contribution critically depends on the validity of the social simulation models being developed, and hence the development of formal and behavior dynamic theory on human-environment interactions requires an iterative process of data collection and model development.

Once the underlying processes have been cross checked to satisfaction, the model can be used as a test bed for either interventions (like policies, information, incentives and so forth) with a simulated population, or for estimating the influence of environmental impacts on such a population (like in adaptation research). Obviously the non-linearities that are typical for dynamical processes in social systems imply that model outcomes should be interpreted with care. Model outcomes should not be considered as predictions of future states, but rather as possible scenarios that may arise given certain assumptions on the underlying behavioral dynamics. Social simulation models can thus be valuable in exploring how behavioral dynamics may give rise to different developing scenarios in behavioral domains. Such scenarios (or “futures”) in application domains can inform scientists and also policy makers of qualitative characteristics of human-environment interactions on a sound scientific basis. In that process, an additional advantage of social simulation is that formalizing theory and empirical data in models requires researchers to be very rigorous and explicit in their assumptions. It thus can be communicated as a whole to the scientific community for scrutiny. Hence social simulation is a tool that genuinely stimulates the interaction between scientific disciplines and helps environmental psychology positioning itself better to make a difference in future developments.

Being a rather new methodology requiring computational skills, only a limited number of psychologists are using social simulation today. This is, we suspect, partly due to the perceived cost-benefit relationship of using that method. An adequate choice of a programming tool can steepen the learning curve considerably. Netlogo (<http://ccl.northwestern.edu/netlogo/>) does not require in-depth programming skills, is free, and comes with a vast library of example models from a wide array of disciplines. It is the ideal tool to take tentative steps with the method, or to use it in teaching. A good reading resource, not only for psychology-affine simulations, is the Journal of Artificial Societies and Social Simulation (<http://jasss.soc.surrey.ac.uk/JASSS.html>). The international

conferences organized by e.g. the European Social Simulation Association (<http://www.essa.eu.org/>) give another good entry point into the field.

3. The papers of this special issue

This special issue presents seven studies where social simulation is being used as a methodology. The issue serves to demonstrate how social simulation as a tool - complementary to conventional empirical and theoretical work - helps in tackling the main challenges that environmental psychologists face. In this special issue you will find a selection of such social simulation models addressing a variety of environmental issues. Different theories are being applied, ranging from specific opinion dynamic processes to integrated behavioral models. The models and their implementation are being described in the papers, but additionally most of the simulation models are available for use on openABM (www.openabm.org). It is a public repository for (simpler) simulation models that lend themselves to be tried out and scrutinized by (even inexperienced) other researchers. Those readers that want to run the models themselves, also in teaching, or want to use the model or parts of the code in other projects are invited to do so.

The paper of Krebs investigates the case of urban neighborhood activation for the support of the elderly during extreme heat waves generated by climate change. Simulation results show that social mobilization can be substantially inhibited because passive habits establish quicker than prosocial behaviors which require successful social coordination prior to becoming habitual. But they also reveal that intervention can provide a window of opportunity for cooperative habits to stabilize and to persist after the intervention.

Schröder and Wolf simulate multi-level network interactions between individual information processing and societal flows of information. Their case study focuses on ex-ante evaluations of suitable campaign strategies for the promotion of car-sharing as an innovative means of sustainable urban transportation.

Sopha, Klöckner, and Febrianti, while investigating the diffusion of natural gas driven vehicles and its promotion by subsidies, compare two decision making theories. One is a rational choice algorithm focusing on car attributes only, the other includes social influence and imitation. The latter seem to offer a better explanation for the pattern observed in a survey with stating vehicle adoption choices.

Kangur, Jager, Verbrugge and Bockarjova address the dynamics of the diffusion of electric and hybrid cars over a period of 20 years. They use an integrated behavioral model (Consumat) to formalize an artificial population based on detailed data of 1795 respondents. Their results advocate for a combination of policies addressing exclusively full electric cars to maximally reduce emissions.

Ernst and Briegel present a spatial explicit simulation of the diffusion of green electricity across Germany. Their psychological decision model is based on extensive data and includes goals, deliberative decisions as well as status quo bias, social milieus, communication over personal networks, and sensitivity towards external events such as price changes or messages from the media.

Janssen and Baggio use social simulation in formalizing alternative theories on cooperation in commons dilemmas to test which one best explains the data obtained from 44 group experiments. Their results demonstrate that there is no single theory that outperforms others in explaining the data, thus illustrating how social simulation can contribute to critically testing the explanatory power of theory against empirical data.

Stefanelli and Seidl focus on the possible long term opinion dynamics concerning the storage of nuclear waste in deep geological

repositories in Switzerland. They show how social simulation offers a possibility to use empirical data in parameterizing a model to explore long-term opinion dynamics of a large heterogeneous population on an environmental relevant issue.

The overall goal of this special issue on social simulation is to provide enough theoretical background and successful examples from the domain of environmental psychology to inform a wider audience of environmental psychologists about the principles of this methodology and its application. This special issue demonstrates that social simulation offers a powerful methodology to translate findings from environmental psychological studies into simulated societies. These simulated societies offer the possibility to systematically study how different assumptions, and policies, may impact the system. Moreover, experimentation with artificial populations may show when social-environmental systems are stable, and under what conditions the coupling of individual and group/societal level may generate self amplifying processes and turbulent processes of change (Nyborg et al., 2016). The editors of this special issue hope to inspire researchers and educators in the field of environmental psychology to think about possible applications of social simulation in their field. This might stimulate further collaborations between environmental psychology and other disciplines dealing with complex environmental problems in future research. As the interest for social simulation is rising in many disciplines, more students get acquainted with the methodology. We thus hope that this special issue will inspire researchers in the field of environmental psychology to consider social simulation as a useful tool for future multi-method projects, and computational social science as a relevant methodological addition to educational programs.

Acknowledgements

We thank the editorial board of the Journal of Environmental Psychology, in particular Robert Gifford, for accepting a special issue on a methodology that is new to most of the readership. We express our gratitude to the reviewers who contributed to the quality of this special issue by carefully and critically commenting on several versions of the included papers.

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Wander Jager*

University of Groningen, University College Groningen, Groningen
Center for Social Complexity Studies, Groningen, The Netherlands

Andreas Ernst

University of Kassel, Center for Environmental Systems Research
(CESR), Kassel, Germany

E-mail address: ernst@usf.uni-kassel.de.

* Corresponding author.

E-mail address: w.jager@rug.nl (W. Jager).