SEM2Agent - A Scheme for the Use of Structural Equation Model Data in Agent-Based Models

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Abstract. As the interest in the use of agent-based models is increasing in the social sciences, so is the need for a standardized way to design, document, and communicate about agent-based models grounded in empirical research. This paper explores the use of structural equation model data as a foundation for the design of agent-based models. Utilizing existing protocols for standardized creation of agent-based models like the ODD protocol, we introduce the SEM2Agent translation scheme, which provides guidance on designing agent-based models grounded in structural equation models in a standardized way. After, we demonstrate the translation scheme and exemplarily design two agent-based models. We found that structural equation models can provide an excellent basis for some components of agent-based models, whereas other components such as the emergent and interactive aspect of the agent-based model have to be designed independently from the structural equation model.

Keywords: Agent-based model · Translation scheme · Structural equation model · Empirical data.

1 Introduction

The history of *agent-based models* (ABMs) spans many decades [23]. To this day, model design differs from modeler to modeler, and models are often hard to compare [24]. Similarly, the way ABMs are described differed and still differs strongly. Modelers specify different types and different amounts of information or do not fully describe the models [14].

As a reaction to this, the *ODD protocol* was created [12–14]. It is supposed to enable other modelers to reuse and replicate a published model to build upon it or test its quality. For models with human agents, similar frameworks were developed to better describe human decision-making and to include empirical data [31, 20, 17]. These frameworks underline the necessity and wish of modelers for an established standardized way to design, document, and communicate agent-based models.

Structural equation modeling, also called causal modeling, is a multivariate modeling technique prominent in the social sciences [16]. We argue that structural equation models (SEMs) describing decision processes are well suited to inform the design of agents for agent-based models. Being composed of multiple linear equations, SEMs can be organically integrated in agent-based model code structures. In this article, we introduce the SEM2Agent translation scheme. The scheme provides guidance on how to use SEMs as a foundation for ABMs in a standardized way. As a demonstration, we use it to design two example ABMs.

2 Related Work

2.1 Principles of Agent-based Models

Aspects associated with ABMs are *emergence* and the trade-off between *simplicity* and *realism* [33]. *Emergence* describes that the system behavior of a model is not directly predictable from the behavior of system parts: Systems are not the pure sum of their individual components, but because the components interact and complement each other, new system behavior emerges that is difficult to predict [9].

ABMs typically consist of three basic components: The *agents* are located within an *environment* and are often connected to each other through a *topology* [18].

Agent-based modeling can be seen as a way of thinking bottom-up and not as a technology. It aims at empirical and normative understanding, theory extension, and methodological improvements. Using agent-based modeling enables gaining insights on the micro- and/or macro-level. The perspectives of each component are listed to describe the system [6].

ABMs can be designed in different ways. First, scientists can base models on existing theories. Then, the model can be used to evaluate and test the assumptions of the theory. In case of deviations, the theory might get updated [32]. Second, modelers can combine theoretical assumptions and empirical results. In this way, they can use empirical sample data to test theoretical or new assumptions. Grounding models in empirical results makes them more realistic [31]. As SEMs exist both for theory confirmation and empirical exploration, they lend themselves well for this second approach.

ABMs do not claim to be fully realistic or to accurately represent reality. However, at the individual level, agent behavior is modeled to be very similar to empirically observed behavior. By visually representing individual behavior, ABMs can qualitatively visualize the emergent behavior of the overall system [25].

Using agent-based modeling, one can analyze systems and patterns from the bottom up and consider heterogeneous agents, which behave according to different behavioural rules. It is also an important characteristic that the models vary randomly [15, 6].

2.2 Empirical Data in Agent-based Models

Qualitative or quantitative empirical data can be used to decide how agent-based models are designed and how decision processes, agent attributes, and behavioral response functions are implemented [31]. There is no agreement yet on whether and how empirical data should be implemented, as well as how its use should be documented and communicated [28, 5, 30]. This lack of unity can lead to vastly different ABM results, even if the same theory and empirical data is used [19].

2.3 Systematic Approaches to Agent-based Model Design

A prominent text-based template for creating and describing ABMs is the *ODD protocol* [14, 13, 12]. A guide for the parameterization of human behavior using empirical data comes from Smajgl et al. [31]. Alternatively, models can be describes using class languages like iStar [10] or BDI language [8].

We consider text-based methods to be the most promising approach to be used by the majority of users. Using natural language ensures accessibility for modelers from diverse backgrounds. Therefore, we chose to base our approach on the ODD protocol [14, 13, 12] and its advancements [20, 17] and on the parameterization framework by Smajgl et al. [31]. We describe them in the following sections.

The ODD+ Protocols. Grimm et al. introduced the *ODD protocol* facilitating the standardized creation of ABMs [14, 13, 12]. The *ODD protocol* guides its users in how to write and read agent-based models in three categories: In the first category, the modelers provide an *Overview* of the model. In the second category, they indicate how they implemented the *Design concepts* defined in the protocol. In the third category, modelers describe other *Details* of the model. The *ODD protocol* facilitates communication within and between different disciplines using mostly natural language [14].

The *ODD+D(ecision) protocol* [20] is an extension that aims to improve the description of models including human decision making and behavior. The *ODD+2D (+Decision +Data) protocol* further instructs modelers on how to specify the use of empirical data in agent-based modeling [17].

Parameterization of Human Behavior in Agent-based Models. Smajgl et al. developed a framework for designing agents using empirical data [31]. They specify six methodical steps to parameterize the agents.

In the first step (M1), modelers define different classes and types of agents using empirical data. Second, modelers specify values for agent attributes (M2) and assign the parameters determining the agents' behavior (M3). Different agent types might also be defined based on attributes or parameters (M4). The last step is the mapping of parameters, attitudes, or agent types to the whole agent population (M5).

2.4 Structural Equation Models as an Empirical Foundation for Agent-based Models

In this chapter, we argue why structural equation models are especially well suited to base agent-based models upon.

Structural Equation Modeling. Structural equation modeling (SEM) is a technique used to understand cause-effect relationships in empirical data and is often used for theory confirmation. For this purpose, covariance-based SEMs are used, while for exploratory purposes variance-based partial least square SEMs are used [11]. In both techniques, two kinds of effects are investigated: The relationships between observed and latent variables (measurement model) and the relationships between the latent variables (structural model).

In structural equation modeling, first, the measurement model is used to calculate latent factors from the manifest, observed variables. Together, the calculated latent factors provide the analyzed variance of the manifest indicators—but adjusted for measurement errors. Then, using the structural model, it is examined how the latent independent variables—here called exogenous variables—influence the latent dependent variables—called endogenous variables in SEM. Exogenous variables stand at the beginning of the model and are not explained by other variables. Endogenous variables are influenced by other variables in the model. With structural equation modeling, it is possible to determine whether one variable influences another variable directly or whether the relationship between the two variables is mediated by another variable [16, 11].

Structural Equation Modeling and Agent-based Modeling as Complementary Methods. As discussed, using empirical data or well-established psychological theories in ABMs enables to model realistic individual behavior.

Because SEMs are models of causal flow, they can be organically integrated in the flow of behavioral rules an agent follows. They provide information about how agents might behave and make decisions on a subsystem level. From this, system behavior can be derived using the ABM. This might be especially interesting when examining gaps between individual and system behavior, and also intra-individual gaps between intention and action. A prominent example for a gap between intention and action on the individual level [29] is the so called *value-action gap* in the context of pro-environmental behavior [4]. Most individuals state that they want to behave in climate-friendly way, but this is not necessarily reflected in their behavior (e.g., vacation flights). Thus, when studying behavior in which a gap exists between individual and system behavior or intention and behavior, a combination of different methods might provide novel insights: While ABMs can map system behavior very well, SEMs are well suited to represent individual behavior.

Especially when considering the behaviors of individuals, it is not easy to predict what macro-level patterns will emerge from the combination of behaviors. It is not possible to simply sum up individual intentions and actions because human behaviors are always influenced by the behaviors of others. Likewise, past (and present) actions influence how people behave in the future [7].

SEMs provide individual-based results on the micro-level. They are not suited to analyze resulting behavior or system patterns. Thus, combining an SEM with an ABM allows analyzing results on the micro- and macro-level. The results of the SEM can be seen as the rules guiding an individual or agent. Following this idea, the results of SEM model can be implemented into the individual agents. The outcomes of the SEM analysis become micro-level assumptions of the ABM, however with a high level of detail and compatible with empirical data. For example, the SEM can provide results about the determinants of environmentally friendly behavior change. This behavior change model could then be used as input for the agents of the ABM. In this way, one can combine the individual-based SEM method to consider the behavior of single individuals and give these behaviors to the individual agents in the ABM to observe the resulting system behavior.

There are a few publications which have already utilized structural equation models in combination with agent-based models (e.g. [27]). In this paper, we propose a systematic approach which we hope will facilitate the rigorous design of agent-based models based on structural equation models.

3 The SEM2Agent Translation Scheme

For our translation scheme, we draw on the ODD protocol [12–14], the ODD+D protocol [20], and the ODD+2D protocol [17] as well as the framework by Smajgl et al. [31] (see Figure 1). We provide suggestions on where and how to include structural equation model (SEM) data.

We propose two possible mutually inclusive ways to ground an agent-based model (ABM) in SEM information: First, SEMs on decision processes and psychological mechanisms can inform the way agents make decisions and process interactions. The SEM variables (or constructs) can be utilized as state variables associated with the agent. The path coefficients (and possibly their confidence intervals and the explained variance R^2) are parameters characterizing the relationship between those state variables. Second, the data underlying the SEM estimation can be sampled to generate initial values for those agent state variables, even if only descriptive summary statistics are available. If desired, sampling from the confidence intervals of the path coefficients can provide more heterogeneity in individual agents, yet still maintain the general overall relationships.

The final SEM2Agent scheme consists of 23 separate steps. In the following, we will shortly set out each step with respect to the use of SEM and related data. For a detailed description of each step, please refer to the original protocols and frameworks.

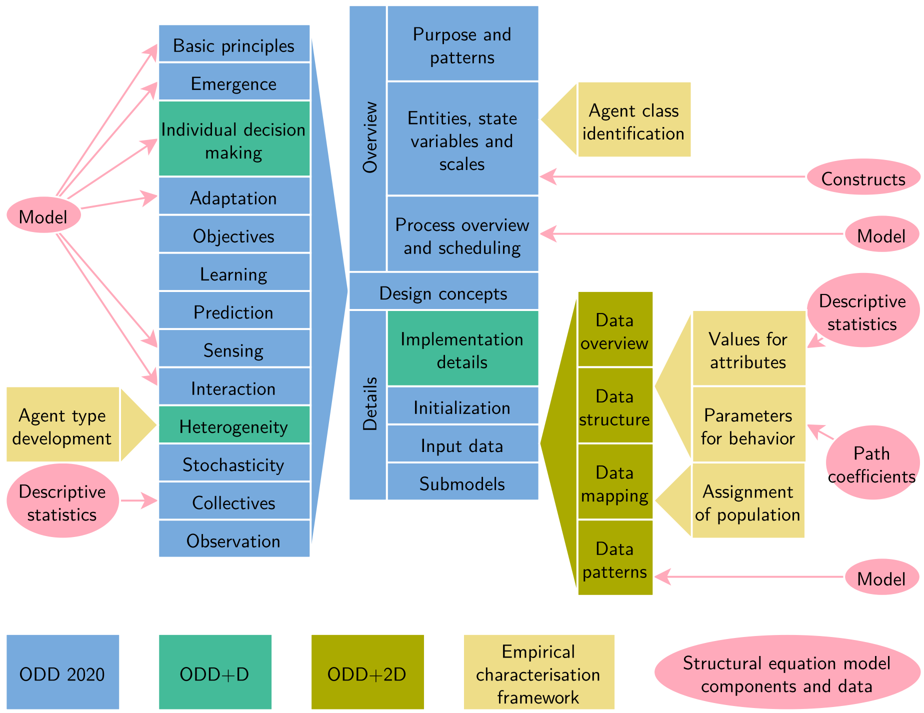

Fig. 1. Structure of the SEM2Agent translation scheme integrated from the different ODD(+) protocols [14, 13, 12, 20, 17] and the empirical characterization framework [31].

3.1 Overview

Purpose and patterns [14] As in the original ODD, the researchers first define what purpose their ABM serves. They also decide what patterns they will use to evaluate the ABM against. If the purpose is not to simply replicate or validate the SEM results, concept and purpose need to go beyond those of the SEM.

Entities, state variables and scales [14, 31] In this section, the researchers describe the entities composing the model. They also name the state variables associated with the model. The state variables of the agents can be, at least partially, derived from the SEM constructs.

Process overview and scheduling [14] The researchers can model the order of processes after the sequence of regression equations in the SEM.

3.2 Design concepts

Basic principles [14] The SEM will be one of the main principles underlying the model design at the agent level. The researchers describe this, as well as other principles the model is based on.

Emergence [14] As every SEM can be described as a system of linear equations, emergence cannot arise from the SEM itself, but from the interaction of agents with each other or with other model entities.

Individual decision making [20] While many SEMs depict decision processes, the level of detail in which decision-making characteristics are specified varies. In describing subjects, objects, objectives and determinants of decision making, the researchers make the implicit assumptions of the SEM explicit and complement them where necessary.

Adaptation [14] As the assumption of a SEM is that all its variables are immutable, if not in their value, then in their existence and relationship with other variables, adaptive agent behavior cannot be derived from the SEM. If adaptation is part of the ABM, it has to be grounded in other theories.

Objectives [14] As with individual decision-making, objective seeking is mostly implicit in SEMs. If explicit objective seeking is to be used in the ABM, it cannot be derived from the SEM.

Learning [14] Similarly to adaptation, learning, which refers to a change of decision-making as a consequence of the agent's experience, cannot be derived from the SEM.

Prediction [14] Prediction as a facet of decision-making is another aspect that has likely to be informed from theory outside the SEM.

Sensing [14] Some characterization on the accuracy of sensing or knowing can be derived from the SEM. For example, a latent variable that measures a person's perception of a factor likely contains some inaccuracy compared to the real value of that factor.

Interaction [14] How agents interact can only partly be informed by the SEM. If the SEM explicitly includes a mode of social influence, this social influence might be modeled via agent interaction in the ABM. But the exact mechanisms of that agent interaction have to be defined independently from the SEM.

Heterogeneity [20, 31] If agents are to be heterogeneous in their decision-making, the researchers can draw from different SEMs. They might use the results of a multi-group analysis.

Stochasticity [14] The researchers can use stochasticity when initializing the model with descriptive data to produce variation in the agent population. They can also use stochasticity to account for variance in variables which is not explained by the SEM.

Collectives [14] Collectives can be modeled based on descriptive findings.

Observation [14] What information the researchers collect is independent of the SEM.

3.3 Details

Implementation details [20] The details of model implementation and potential availability of model code are independent from the SEM.

Initialization [14] The researchers can initialize state variables based on SEM variables using the associated descriptive statistics, possibly applying a stochastic sampling method.

Input data: Data overview [17] For the input data from the SEM as well as other data sources, the researchers describe the origin, level, and structure of available data.

Input data: Data structure [17, 31] For the SEM and other input data sources, the researchers describe the data structure, their format, and how they are linked. Specifically for the SEM, the researchers lists the regression equations and R^2 values for all endogenous variables, as well as descriptive results for all variables.

Input data: Data mapping [17, 31] After outlining the original structure and format of the data, the researchers describe which of that origin data is selected and how it is transformed for its use in the ABM. The researchers can derive behavioral parameters from the path coefficients. If descriptive results are available, they can use these to generate (initial) values for agent attributes. They should then also describe how values are assigned to the agent population. The researchers might scale both variable values as well as path coefficients to ensure a stable range of target values. We suggest to normalize path coefficients so the sum of their absolute values is exactly one, and limiting the range of variable values -1 to +1.

Input data: Data patterns [17] The researchers describe patterns of the data in the source material. For SEMs, the most obvious pattern is the structural model.

Submodels [14] The researchers might include submodels, one or several of which might be based on a SEM. If they do, they describe them using a similar structure as outlined for the overarching ABM.

4 Scheme demonstration

In this section, we demonstrate the application of our scheme for two ABMs. The first model considers the relationship between employee stress and company success [26]. The subject of the second model is the adoption of a new environmental policy program among California farmers [22]. We strived for a simplistic approach in both models. For the sake of brevity, we only give a short overview of the modeling process, the results and the suitability of our scheme. We provide the full protocol and results for both models as well as the complete code as supplementary material.[1]

4.1 Employee motivation model

The first model considers the influence of stress, niceness of fellow employees,, employee relationships, and employee satisfaction on (elder) employees' motiva-

[1] Protocol and results can be found at `https://digitalemuendigkeit.github.io/SEM2Agent/`. The repository containing the code can be accessed at `https://github.com/digitalemuendigkeit/SEM2Agent`.

tion at the workplace. In turn, it shows how successful a company is when it shields employees from company stress or not. We integrated the four (latent) variables (*stress*, *employee relations*, *employee motivation*, and *employee satisfaction*) from the SEM established by Rozman et al. [26] as properties of the agents into our ABM. All properties ranged from -1 to 1.

We also added a *fraction of nice employees*, which indicates how many agents in the model are marked as *nice*. This influences how employees perceive relations. For the environment, we added the *company stress* and the *company success*, both ranging from -1 to 1, to the agent-based model. Lastly, we varied between different levels of employee *stress reduction*: When we set the *stress reduction* to low, the company did not guard their employees from the *company stress* and the employees were exposed to the full range of stress. Using a high *stress reduction* leads to an attenuated influence of *company stress* on employee agents.

We conducted experiments varying some of the aspects described above. We ran each model 500 times. In each experiment, the model ran for 50 steps representing 50 weeks. Figure 2 shows the results of one of our experiments. Here, we initialized our model with negative starting conditions and with a high *stress reduction*.

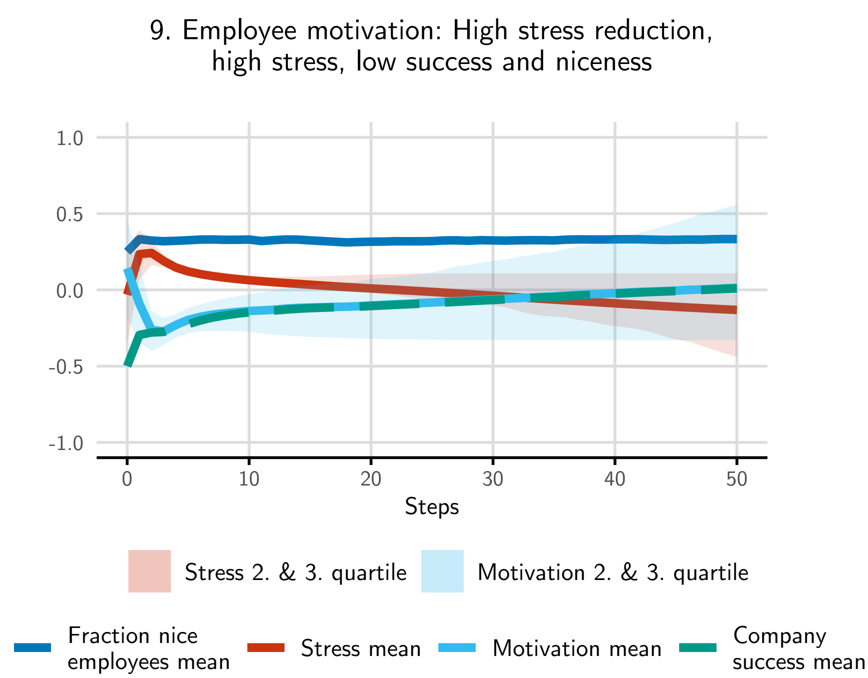

Fig. 2. Results of experiment 9 with negative starting conditions and high stress reduction; means and quartiles are calculated over all 100 agents and 500 iterations

In the beginning, there were only 25 % *nice* employees, the *company stress* was medium-high (0.5) and the *company success* was low (-0.5). The *stress* of the employees decreased over the model runs, the *motivation* of the employees and the company success increased. The amount of nice employees remained roughly constant.

4.2 Environmental program participation model

The second model simulates the participation of California farmers in a fictitious new climate policy program. It is grounded in a structural equation model on the perception of climate change and climate policy risks in California farmers [22]. The structural equation model posits *climate change experience*, *past policy experience*, *climate change belief* and *climate change risk* as (indirect) predictors of *government program participation*. Similar to the *Subjective Norm* variable from the *Theory of Planned Behavior* [1], we added a social interaction component: Normative pressure of neighboring agents participating in the program also increases program participation intention. The *climate change experience* state variable was calculated based on empirical drought data from the same county where the SEM data was collected [21].

For our experiments, we ran each model 500 times. The model ran for 10 steps, representing 10 years. All variables except fractions can take on values from -1 to +1. We varied the fraction of initial program participants (default: 25 %), the fraction of neighbors needed to exert normative pressure (default: 50 %), and the quality of the policy program (default: 0.4). The model results for the default conditions are displayed in figure 3.

Varying any of the model parameters led to changes in both policy experience and fraction of participants. Increasing the fraction of participating neighbors needed for normative pressure to 100 % resulted in the overall lowest participation. A model similar to this could be used to both validate a structural equation model against existing participation data, or to inform policy decision when introducing a new program.

5 Discussion and Outlook

Using two example models, we demonstrated that SEMs can be used to systematically ground ABMs in structural equation models using the SEM2Agent scheme. The SEM2Agent scheme simplifies the standardized design of ABMs using results from SEMs as a data basis. It provides guidance on how to ground agent behavior on established theory. Thus, it can help to bridge the gap between sociological exploration of group processes and psychological examination of individual patterns of decision-making and behavior. To put it differently, it enables profound analyzes of research questions considering problems on the micro- and macro or the individual- and system-level combining an individual-based method (structural equation modeling) with a system-oriented method (agent-based modeling).

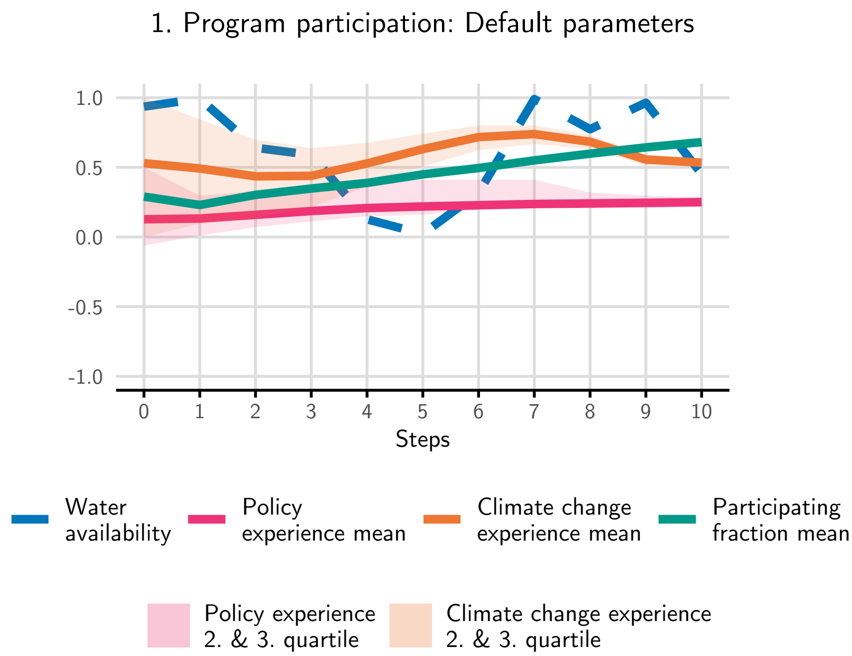

Fig. 3. Results of the policy adoption model with default conditions; means and quartiles are calculated over all 100 agents and 500 iterations

The first crucial requirement for this approach is that a valid SEM with high quality data for the research question exists. However, as SEM and open data are being used increasingly in social science research the availability of suitable SEMs and data is expected to increase as well. If for a specific research question no SEM and data exist, extensive prior research has to be conducted (i.e., theory development, data collection, structural equation modeling).

The second requirement for using complex models such as SEM to inform micro-structure in ABM is that the individual SEM contains exogenous and endogenous variables that lend themselves well to be linked to the input into the agent and the agent's behavior. If there is only one point where ABM variables interact with what were originally the SEM variables, i.e., only one point of input, the sequence of subsequent variables linked by SEM parameters can be described as a linear transformation. In this case, including all variables and parameters is obsolete.

A benefit of this approach is that the SEM then allows for fine-tuning the agents' internal workings according to empirical findings on a causal level. Another benefit is that several validation points in agent attributes now become available that provide direct means of empirical measurement (i.e., SEM indicators). This includes being able to have introspection into features such as attitudes that themselves do not reflect immediately on behavior.

Especially when considering human behavior and behavior change, it is pivotal to understand both which factors influence how an individual behaves and why, which group processes result from this, and what the individual behavior means for the society. Current examples for this are behavioral responses to large-scale crises like pandemics and global warming, but also individual health behavior [3, 34, 2].

In designing the SEM2Agent scheme, we found that not every component of the ABM can be simply translated from components of a SEM. At a minimum, the modeler needs to supplement the SEM data with decisions on how to model space, time, and interaction between agents and other agents, or agents and their environment. As an SEM can be described as a system of linear equations, on its own, it cannot lead to emergence. Instead, emergent effects can be the result of agent interactions or of feedback loops.

After introducing this first version of the SEM2Agent scheme, we hope that many modelers can utilize our approach and will benefit from this addendum to existing systematical approaches to design ABMs. We recommend that other researchers using this approach should adhere to the ODD+ protocol with our adaptations to report their utilization of SEMs in ABM. At least reporting of the individual SEM including path coefficients, confidence intervals, and explained variance seems necessary.

We also hope to improve and further develop the scheme in the future. Therefore, we look forward to feedback from the agent-based modeling community. As a next step, we plan to utilize the SEM2Agent scheme to design an ABM grounded on our own research in the field of behavior change.

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Supplementary material

The supplementary material for this paper is provided as a website:
`https://digitalemuendigkeit.github.io/SEM2Agent/` The repository containing the model and website code can be accessed at `https://github.com/digitalemuendigkeit/SEM2Agent`.

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