Simulating Psychological Experiments: An Agent-Based Modeling Approach

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***Abstract*—Analyzing human behavior in organizational structures becomes more difficult due to a rising complexity of teamwork processes and interdependencies between team members. The paper proposes an interdisciplinary approach of agent-based modeling and laboratory experiments from organizational psychology to overcome the shortcomings of each discipline and to allow a more detailed and realistic view on teamwork in theory and practice. To demonstrate the benefits of simulating psychological experiments, the replication of a small group experiment for analyzing the distribution of meta-knowledge is conducted. The results from simulation and experiment are plausible.**

***Keywords*–Agent-Based Modeling; Social Simulation; Team Mental Models; Meta-Knowledge.**

I. Introduction

Due to rising complexity of teamwork processes, knowledge distribution and interrelationships between team members, understanding human behavior in organizational structures becomes more difficult. To overcome the shortcomings in analyzing teamwork, an interdisciplinary approach of Agent-Based Modeling (ABM) and theories from organizational psychology is promising to gain new insights. From a psychological perspective, theories and concepts of teamwork can be analyzed in laboratory experiments. The major drawbacks of these experiments are restrictions due to their limitations such as financial ones. ABM can be used to overcome the shortcomings and complement laboratory experiments, e.g., their design and scalability [1]. From an ABM perspective, modeling teamwork experiments can enable a more detailed comprehension of human behavior and should allow for more realistic agent architectures. One major characteristic of ABM is modeling behavior with specific actions which enables causal explanations of an observed pattern. However, in psychological research, experiments are commonly used to reveal correlations between conditions and measurements. Therefore, replicating a teamwork experiments with ABM supports psychologists to observe how behavioral team patterns emerge from individual actions [2].

The contribution of this paper is twofold: (1) how can ABM researcher and psychologists benefit from each other as well as what prerequisites are necessary to model and simulate psychological experiments and (2) presenting a study of replicating a teamwork experiment, which should clarify challenges and opportunities. The replicated study in this paper focuses on the different measurements (correlation vs. causality) in psychological research and ABM.

The remainder of this paper is structured as follows. In Section II, psychological research methods in a simulation context are shown. Section III presents an experimental study which utilizes a measurement: the Team Mental Model index (TMM Index) to analyze the distribution of meta-knowledge in teams and its consensus among team member. Consequently, an agent-based model of the TMM Index experiment is shown in Section IV. In Section V, a comparison of the results from experiment and simulation is given.

II. Simulating Psychological Experiments: Foundations and Challenges

Psychological research focuses on human cognition and behavior. In that context, experiments reveal correlations between controlled conditions and observable behavior (independent and dependent variables). Those correlations represent generalizable behavioral patterns, which can be utilized to indirectly draw conclusions about psychological constructs of human cognition for individuals and small groups.

Various scholars have proposed computer simulation in general and ABM in particular as a method in the field of psychology. However, these simulation studies can only provide insights into artificial systems as modeled and represented in a computer. Consequently, two questions arise. Firstly, why should psychological experiments be simulated since a computer does not exhibit human behavior? Secondly, how should these experiments be simulated, i.e., what are challenges and existing practices of modeling and simulating psychological experiments? The following two sections explore these questions and provide an overview of existing research in that area.

A. Why Simulate Psychological Experiments?

There are three main benefits of simulating psychological experiments. These roughly correspond to the following three phases of a computer simulation study.

1) The model development phase
2) The experiment and simulation design phase
3) The experimentation and results analysis phase

Activities in each of these simulation phases can both contribute to psychological research. Vice versa, simulating psychological experiments throughout these phases can also provide novel impulses for social simulation as a research method.

The first benefit of simulating experiments is their contribution to formal procedures and theory building. Due to

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the necessity to formalize the experiment in a computational model, such a simulation enforces a rigorous formulation of independent and dependent variables as well as the underlying theoretical constructs and their interrelations. The variables denote which conditions are manipulated during an experiment and which measurements are taken. These measurements are then used to conclude on underlying theoretical constructs which cannot be observed directly. However, in a simulation, these must be explicitly modeled in order to create observable effects. Consequently, developing simulation models requires explicating these constructs in a computable form. This supports precise descriptions of both psychological experiments and theory. In turn, precisely formalized psychological theory and cognitive or behavioral models can help building better social simulations. To be realistic, such simulations must be grounded in actual human cognition and behavior. Psychological experiments provide this grounding.

The second benefit covers the design of both experiments and simulations. In organizational as well as social psychology, experiments frequently involve groups of people and their interactions. To enable statistically relevant conclusions, each combination of independent variables must be sampled often enough. Every test must be repeated with at least 30 groups. Given a minimal group size of three persons, this kind of research requires at least 90 test persons per experiment condition; e.g., 360 persons for a simple 2x2 experiment design. Thus, it rapidly becomes unfeasible to scale up either the number of independent variables or the group size. Simulating experiments can help solve this problem since the number of agents in a model can be scaled up easily. If such a simulation is grounded in actual experiments, scaling it up may reveal interesting effects in the observed artificial system. These can then be used to design further experiments to verify or reject those findings. The experiments can then be reduced to the specific conditions that produce the respective effects in the simulation. Hence, the problem of scalability is alleviated. Moreover, the results provide additional validation of the simulation model or reveal the requirement for its refinement. This leads to a iterative experimentation process in which psychological experiments provide new hypotheses for the design of simulation studies and simulation results inspire additional laboratory experiments.

The third benefit of psychological experiment simulation is its contribution to the analysis of either method's results as well as to deriving and testing theoretical concepts. In psychology, experiments are used to reveal correlations between manipulated conditions and measurements to conclude on underlying theoretical concepts. However, these correlations cannot provide causal explanations of the observed effects. By contrast, computer simulations require the modeling of causality. Such a model provides a possible candidate for an explanation. While its correctness cannot be proven, it can be assumed to be feasible as long as it can replicate experiment results. Therefore, simulating experiments helps both developing and testing psychological theory as well as verifying measurements and results of social simulations.

Nonetheless, there are several challenges to be overcome for achieving the aforementioned benefits. The following section discusses existing research and identifies the challenges which will be addressed in the remainder of this paper.

B. Related Work

In order to simulate psychological experiments, it is necessary to transform these experiments into computational models and social simulation studies. Despite the recognition of ABM as a research method in (organizational and social) psychology, few researchers have attempted this so far. Instead, the majority of existing work focuses solely on simulation models of teamwork processes or on cognitive agent architectures. Thus, there is little work available on the challenge of transforming experiments into simulations and vice versa. Nevertheless, the following works in this context are noteworthy.

The majority of related work focuses on the development and exploration of conceptual models for explaining behavioral processes. This approach is primarily used for theory building by studying how the modeled interactions change within a simulation. It usually starts with a theoretical concept of cognition and behavior for the addressed application area which is then transferred into a computational model. For instance, Ren et al. model the meta-knowledge in teams to systematically explore when it is beneficial to know what other team members know in an agent-based simulation [3]. Similarly, Smith & Collins use such a simulation to analyze the impact of social contexts on distributed cognition processes [4]. Thus, both of these studies focus on model development to gain a more thorough understanding of theoretical concepts and their interplay.

Another line of research covers on the simulation design phase. Instead of being strictly theory-driven, those approaches focus on parameterizing individual agents from survey data. They use this data for creating unique profiles, which control the respective agents' decision-making in a social simulation [5]. While such an approach is more common for analyzing large populations [6], Kangur et al. make use of that technique to model influence factors and decision-behaviors for the acceptance of electric cars [7]. This contribution provides interesting insights into the transfer of variables in the form of survey items into parameters for artificial agents in a simulation setting.

The aforementioned approaches follow the recommended pattern of developing a model from theoretical concepts, implementing it, and parameterizing it using empirical data [2] [8]. However, none of them combines simulations with laboratory experiments. In that regard, Grand et al. complement those works by starting from a theory-driven model and then conducting an experiment to verify that model [9]. They first analyze processes of knowledge emergence in teams in a computer simulation and then compare the results with those gained from experiments with human subjects. Consequently, they contribute to the results analysis phase of experimentation and simulation.

While the discussed related work covers all of the benefits of simulating experiments, a direct replication of an experiment in a simulation has not yet been attempted. Especially the advantage of scaling up experiments and exploring different settings in a simulation for further experiment design remains unused. To achieve that, it is necessary to transform the settings of an existing experiment into simulation inputs and outputs similar to using survey data for agent parameterization. In addition, the available information and the decision-making of these agents must be specified. To that end, an appropriate abstraction of knowledge and interaction between these agents

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is required. Only then can the resulting model be used to replicate an experiment as well as varied to explore alternative settings. In the following, such a study is presented which shows how these challenges can be met.

III. Application: Team Mental Models for Expertise Location

In order to show the benefits and challenges of simulating psychological studies, an experiment is needed with: (1) a remote set of variables and (2) with relevance for ABM. Therefore, we choose an experiment which analyzes the distribution of meta-knowledge between team members. For team processes the knowledge of each team member is important to team performance [10]. Besides task related knowledge, the perspective of ”who knows what in the team” (meta-knowledge) is also essential. In the past, studies showed positive effects of high meta-knowledge and team performance [11] [12]. Therefore Ellwart et. al. developed a valid and economic measurement for expertise location in organizational context, the TMM Index [13]. They conducted a study which validates the TMM Index in an experimental as well as a longitudinal field study. The TMM Index is a measure of team mental models based on the location of team member expertise. The measure integrates the quality of meta-knowledge and team consensus of within-team expertise. TMM is a subjective measure of individuals’ perceived knowledge of team members’ expertise (e.g., ”I have a good ’map’ of other team members’ talents and skills”). Replicating the TMM Index experiment in an ABM has two benefits. On the one hand, with the use of ABM it is possible to analyze different experiment setups and examine if the same effects hold for e.g., larger group sizes. Therefore a plausible agent-based model is needed. On the other hand, teamwork plays an important role in ABM. In an ABM a team of agents can work together solve a particular task cooperatively. To that end, agents need a mutual beliefs of the skills and knowledge of other agents to coordinate successfully and efficiently [14]. Especially in recognizing the need to solve a task cooperatively, meta-knowledge can enhance the process. A measurement which indicates the quality of meta-knowledge is desirable for agent-based systems.

The original experimental study (N = 120, 40 teams) was conducted with university students. Participants worked in three-person teams to solve a decision-making task. The experimental task described the setting of working at a company that analyses weather data to evaluate travel routes and give recommendations to customers. Each participant received specific customer requests regarding three possible travel routes. The routes each consisted of three different stations. Each station was described by three weather properties (e.g. wind, temperature, and rain). Each participant was assigned expertise for one specific weather property, e.g. expertise for temperature, which included all information concerning the temperature at a given location. Expertise information was only visible to the assigned expert. Information concerning the other participants’ expertise was presented as missing values. In order to create interdependence between team members and to process a customer request (e.g. customer 1: warm, dry, calm weather for swimming), all team members had to exchange information. Team members had to solve the tasks individually while cooperating concerning information exchange, which was crucial for processing a customer request. The experiment consisted of three phases. In the first phase each participant received individualized information about their expertise, weather properties, as well as the customer requests. In the second phase participants communicated via email to get the necessary information from other experts. In the third phase, each participant chose the best travel route for their customer request. In Figure 1, the travel routes which where used in the experiment are shown.

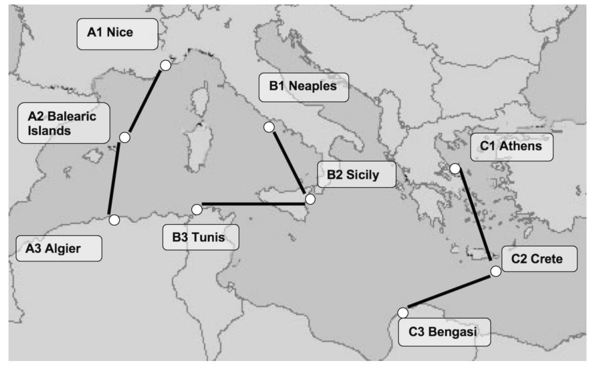

Figure 1. Travel Routes in Group Experiment

In order to validate the TMM Index, meta-knowledge and consensus about meta-knowledge was manipulated in a 2x2 design (”high” vs. ”low” meta-knowledge). This resulted in (i) teams with high quality of meta-knowledge and high team consensus (all participants knew which team member received information and knew that all other team member received this information); (ii) teams with low meta-knowledge and high consensus (no participants received information about the expertise location but all participants knew that no one else received this information); (iii) teams with high meta-knowledge and low consensus (two participants received information about the expertise of other team members but no one was given information about what other team members were/were not told); and (iv) teams with low meta knowledge and high consensus (only one of the three team members received expertise information but all were informed that only one member received said information and were told which member).

The TMM index used in the laboratory experiment is based on a 7-point Likert-scale and is calculated using four items (”I have a good ’map’ of other team members’ talents and skills,” ”I know which team members have expertise in specific areas,” ”I know what task- related skills and knowledge each team member possesses,” and ”I know who on the team has specialized skills and knowledge that are relevant to me”). The calculation of the TMM Index is defined as follows:

$$TMM\ Index = \frac{\sum_{i=1}^{n} x_i}{n} - \sqrt{\frac{\sum_{i=1}^{n} (x_i - \mu)^2}{n}} \quad (1)$$

The index results in the subtraction of the mean value of the survey and the standard deviation and therefore also defined on a 7-point scale. The main hypothesis for the studies is to show if the TMM Index differentiates between teams with high knowledge and high consensus versus high knowledge and low consensus as well as between teams with low knowledge and low consensus and low knowledge and high consensus. The results of the experiment show that the hypothesis can be verified and the index is sensitive to meta-knowledge and consensus (for more detailed results see Section V).

IV. Agent-Based Model for Simulating Meta-Knowledge Distribution

In theory, subjective measurements from participants in a laboratory experiments are based on theirs observations from underlying processes or their knowledge combined with emotions. The original study implemented the TMM as a subjective measure, however in ABM, the TMM Index has to be based on objective knowledge or behavior (e.g., how agents communicate between each other). For reasons of simplification our first simulation only focused on the effects of high vs. low meta-knowledge on TMM Index. Thus, the goal of the ABM was to investigate whether the (objective) TMM Index in the simulation shows a similar sensitivity to manipulated changes of meta-knowledge as the perception based measure in the original experiment. The agent-based model is structured according to the setup of the laboratory experiment. In Figure 2, the components of the ABM are shown. On the left hand side, the input parameters for model configuration are shown. These parameters are based on the laboratory experiment and its scalability potential. On the right hand side, the output parameters, which are used to measure the TMM Index, are shown. In the center, the agent behavior is depicted which is modeled like the participants' behavior from the experiment. The agent's decision-making process is described in the next paragraphs detailedly.

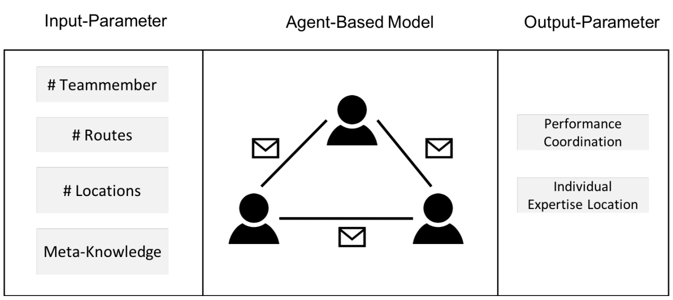

Figure 2. Agent-Based Model for Expertise Location

One major disadvantage of laboratory experiments is their limited scalability due to e.g. personnel or financial limitations. Therefore, the input parameters of the model are the number of team members, number of routes, number of locations, as well as actual meta-knowledge to analyze the results for larger team configurations. The output of the simulation is the TMM Index. The agent-based model itself consists of reactive agents with a representation of meta-knowledge. The knowledge about the expertise location for an agent is defined as follows for $\forall w \in Weatherproperty$:

$$Expertise(w) \rightarrow \begin{cases} Agent\ a; & a\ is\ an\ Expert\ for\ w \\ \emptyset; & guessing\ an\ Expert \end{cases} \tag{2}$$

For every team member each agent knows if they are experts for a particular kind of weather data. This representation determines if an agent has high or low meta-knowledge. In a case of high meta-knowledge, individual agents know exactly which team member holds what kind of weather information. In case of low meta-knowledge, an agent has no information concerning the expertise of other team members. Besides meta-knowledge, each agent has knowledge about weather conditions for different locations on travel routes. The following example in 3 shows the knowledge for a travel route consisting of three different location and each location is describes by three different weather properties.

$$\text{Location} \times \text{Weatherdata} = \begin{bmatrix} -1 & 5 & -1 \\ -1 & 2 & -1 \\ -1 & 6 & -1 \end{bmatrix} \tag{3}$$

The example shows the knowledge of an expert for the second weather property, e.g., rain. The evaluation of a weather property for locations is represented by a value from 1 to 9 which describes the suitability of this location for a specific customer request. A higher value shows a higher similarity. A value of -1 denotes missing information. The overall evaluation value for a route is the sum of the single ratings of the weather properties. L denotes the set of Locations and W denotes the set of weather properties:

$$RouteValue(R) \; = \; \sum_{i=1}^{L} \sum_{j=1}^{W} r_{ij} \tag{4}$$

The route with the highest overall rating is proposed to the customer. In order to calculate the route ratings for a customer request each agent can perform different actions which are modeled in the process from Figure 3:

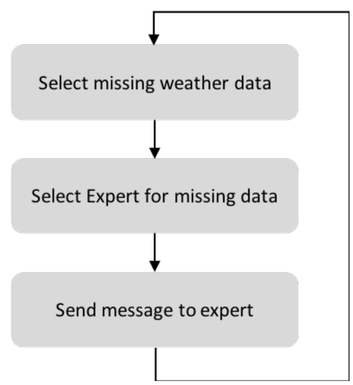

Figure 3. Process of Requesting Expert Information

The process is iterative and ends if an agent has no missing weather data left or has requested this information. In the second step the meta-knowledge determines which expert is requested. If an agent has no information about the expertise location, i.e., has low meta-knowledge it messages every team member. In Figure 4 the processing of messaging is shown. As communication protocol between agents FIPA ACL is used. In order to manage the information exchange agents use FIPA performatives. In this scenario "request", "inform" and "refuse" are applied. Each agent is able to get requests on missing information as well as informs on requested information. In case of a refuse, which means the requested information cannot be provided no action is performed. If there is no missing information left in the knowledge base, then each agent calculates the best route for the customer request.

The main issue of measuring the Index is to transform the subjective measure (4 item survey) into an objective

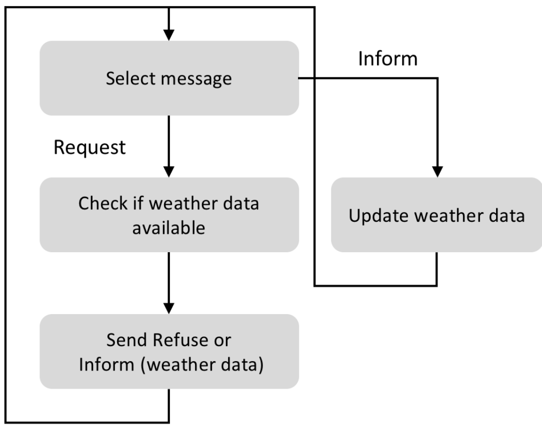

Figure 4. Processing Messages in Agents

measurement. To that end, the individual expertise of an agent is compared to the actual knowledge distribution to cover the 4 item measurement. Besides that, in the laboratory experiment, the highest correlation of TMM Index was measured with the coordination performance. Therefore, the TMM Index calculation in the simulation is based on the average of individual versus actual expertise location distribution (equation 5).

$$Expertise_a(w) \rightarrow \begin{cases} 1; & if\ indivual\ and\ actual \\ & Expertise\ are\ equal \\ 0 & no\ match \end{cases} \qquad (5)$$

The actual TMM Index in the simulation is calculated as the difference of the mean average of the expertise matches and their standard deviation multiplied by the coordination performance. The coordination performance is represented as the ratio of positive requests and total amount of messages. It is used as an indicator for the performance of the underlying teamwork process. In order to test the model's plausibility to represent the TMM Index, the next Section show results from simulating the original experiment.

V. RESULTS AND DISCUSSION

The simulation model is implemented in Java using the Repast Simphony Framework. To test for comparability and plausibility of the two methods, we compared simulation based TMM Index scores in the two conditions (high vs. low meta-knowledge) with TMM Index scores from the original study. The results are described in Section V-A. Additionally, the examination of the models behavior regarding the group size is shown in Section V-B.

A. Psychological Experiment versus ABM Simulation

In order to compare the results from the original experiment and the ABM, the simulation uses the same configuration (3 routes, 3 agents, 3 locations per route as well as high / low meta-knowledge). In case of a high meta-knowledge, each agent knows exactly which other agents are experts for. In case of low meta-knowledge there is no information about the expertise location provided. To measure the equivalence of simulation and experiment, the simulation output was transformed to a 7-point rating. The simulation was executed 1000 times. Simulation results are displayed in Table I.

TABLE I. TMM INDEX RESULTS ORIGINAL EXPERIMENT AND ABM SIMULATION

	Experimental Manipulation	
	Low Meta-Knowledge	High Meta-Knowledge
Subjective TMM Index in original experiment	3,05	4,36
TMM Index in ABM Simulation	2,64	7,00

Similar to the laboratory experiment, the TMM Index calculated in the simulation can distinguish between high and low meta-knowledge, with a lower TMM Index in the low meta-knowledge condition and a high Index in the high meta-knowledge condition (low meta knowledge: experiment 3.05, simulation 2.64; high meta-knowledge: experiment 4.36, simulation 7.00). In the high meta-knowledge condition, the simulation results overestimated the TMM Index. This is due to the direct measure of TMM used in the simulation. In contrast, the experimental study used a subjective measure of participants' perceived TMM. Unsurprisingly, with complete agreement of knowledge of expertise location in the ABM simulation, high meta-knowledge teams reached the maximum score of 7.00 on the TMM Index with zero standard deviation. An overview of the results is shown in Figure 5. In the low

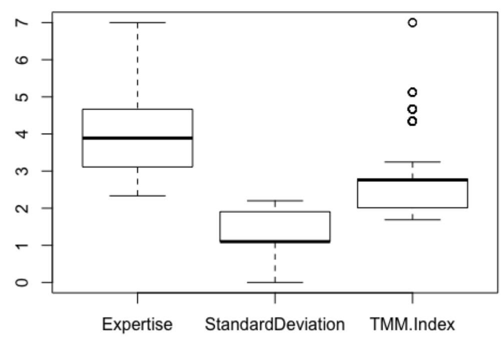

Figure 5. TMM Index Results of Simulation with Low Meta-Knowledge

meta-knowledge condition, the simulation based TMM Index was lower compared to the experimental results. Thus, we presume the different methods of measurement and abstraction caused the described differences in TMM Index. Moreover, the experiment measured a larger set of variables as the simulation model. Concerning the deviation of the meta-knowledge distribution, the computed results show similar characteristics (mean deviation simulation 1,23 and Experiment 1,36). Consequently, choosing an expert at random fits the observations of the empirical study for low meta-knowledge. Nevertheless, the

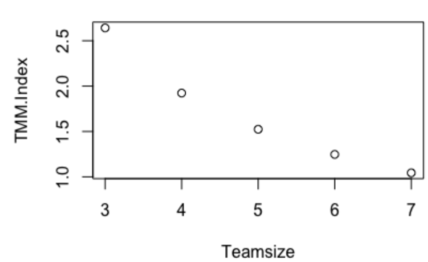

Figure 6. TMM Index results with increased Number of Group Members

results show that it is possible to transfer the concept of meta-knowledge measurement to agent-based systems. The simulation results for low meta-knowledge showed high consistency with the experiment and are plausible according to the concept of TMM Index.

B. Increasing sample size with ABM

In further simulations, we investigated how the TMM Index would change for low meta-knowledge teams with a varying number of team members (team size of 3 to 7 individuals; results are shown in Figure 6). Results show that with an increasing number of team members, the TMM Index decreases. In smaller teams, agents are more likely to select the correct expert at random as the number of possible experts is also smaller. Additionally, the ratio of coordination performance is decreasing due to an increased number of team members.

In total, the result for scaled experiments are plausible in the way that missing meta-knowledge has more negative effects on a team's performance than in smaller groups. The scaled experiment results show that the effect of an objective measurement of the TMM Index can distinct meta-knowledge distribution among team members more clearly. Consequently, measuring an objective TMM Index in the next laboratory experiment could produce more accurate results.

VI. Conclusion and Future Work

Using agent-based modeling to complement psychological research is a promising approach with up- and downsides. This paper presents an ABM which models a psychological experiment on meta-knowledge distribution in small groups. The experiment is used to validate the TMM Index, which is a subjective measurement to distinguish a team's meta-knowledge as well as its consensus about this meta-knowledge. In order to calculate the TMM Index for an agent-based simulation model it is objectified so that causal relationships between a team's performance and meta-knowledge could be shown. The TMM Index calculated from the simulation output is able to differentiate high and low meta-knowledge. Additionally, the simulation experiments revealed that the TMM Index can distinguish between high and low meta-knowledge in teams with larger group sizes, too. Due to the model's assumptions and restrictions, the TMM Index simulation results are plausible but overestimate the index. The major challenge in replicating this experiment is the transformation of the subjective TMM Index measurement to an objective one which represents a shift in not only measuring correlations but causality of teamwork processes and meta-knowledge. The presented study in this paper is a first step towards the vision of simulating psychological experiments realistically.

Future studies should aim to test if a more complex agent architecture is able to reproduce the results more accurately by integrating a consensus component in agents with different manifestations of meta-knowledge in form of different or mutual beliefs is promising. Moreover, ABM can not only be used to support design, formalization and analysis of experiments but complement conducting experiments. In a hybrid experiments with a valid agent-based model humans can interact with agents [15]. Such an approach could overcome limitations of laboratory experiments especially in formalizing measurements as well as modeling causality.

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References

[1] I. J. Timm et al., "Towards multiagent-based simulation of knowledge management in teams." in Flexible knowledge practices and the Digital Workplace (FKPDW). Workshop within the 9th Conference on Professional Knowledge Management, M. Leyer, A. Richter, and S. Vodanovich, Eds. KIT: Karlsruhe, 2017, pp. 25–40.

[2] E. R. Smith and F. R. Conrey, "Agent-based modeling: A new approach for theory building in social psychology," Personality and social psychology review, vol. 11, no. 1, 2007, pp. 87–104.

[3] Y. Ren, K. M. Carley, and L. Argote, "The contingent effects of transactive memory: When is it more beneficial to know what others know?" Management Science, vol. 52, no. 5, 2006, pp. 671–682.

[4] E. R. Smith and E. C. Collins, "Contextualizing person perception: Distributed social cognition." Psychological Review, vol. 116, no. 2, 2009, p. 343.

[5] T. Balke and N. Gilbert, "How do agents make decisions? a survey," Journal of Artificial Societies and Social Simulation, vol. 17, no. 4, 2014, p. 13.

[6] N. E. Williams, M. L. OBrien, and X. Yao, "Using survey data for agent-based modeling: design and challenges in a model of armed conflict and population change," in Agent-Based Modelling in Population Studies. Springer, 2017, pp. 159–184.

[7] A. Kangur, W. Jager, R. Verbrugge, and M. Bockarjova, "An agent-based model for diffusion of electric vehicles," Journal of Environmental Psychology, vol. 52, 2017, pp. 166–182.

[8] J. C. Jackson, D. Rand, K. Lewis, M. I. Norton, and K. Gray, "Agent-based modeling: A guide for social psychologists," Social Psychological and Personality Science, vol. 8, no. 4, 2017, pp. 387–395.

[9] J. A. Grand, M. T. Braun, G. Kuljanin, S. W. Kozlowski, and G. T. Chao, "The dynamics of team cognition: A process-oriented theory of knowledge emergence in teams." Journal of Applied Psychology, vol. 101, no. 10, 2016, p. 1353.

[10] S. W. Kozlowski and G. T. Chao, "The dynamics of emergence: Cognition and cohesion in work teams," Managerial and Decision Economics, vol. 33, no. 5-6, 2012, pp. 335–354.

[11] J. R. Austin, "Transactive memory in organizational groups: the effects of content, consensus, specialization, and accuracy on group performance." Journal of applied psychology, vol. 88, no. 5, 2003, p. 866.

[12] A. B. Hollingshead, "Distributed knowledge and transactive processes in decision-making groups." in Composition., ser. Research on managing groups and teams, Vol. 1. US: Elsevier Science/JAI Press, 1998, pp. 103–123.

[13] T. Ellwart, U. Konradt, and O. Rack, "Team mental models of expertise location: Validation of a field survey measure," Small Group Research, vol. 45, no. 2, 2014, pp. 119–153.

[14] M. J. Wooldridge, Reasoning about rational agents. MIT press, 2000.

[15] L. Reuter, J. O. Berndt, and I. J. Timm, "Challenges of simulating teamwork in organizational scenarios," in 2017 Winter Simulation Conference (WSC), Dec 2017, pp. 4542–4543.

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