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CREDIBLE AGENT-BASED SIMULATION – AN ILLUSION OR ONLY A STEP AWAY?

Bhakti Stephan Onggo

Centre for Operational Research, Management
Sciences and Information Systems (CORMSIS)
University of Southampton
Southampton, SO14 1BJ, UK

Levent Yilmaz

Computer Science and Software Engineering
Auburn University
Auburn, AL 36849, USA

Franziska Klügl

School of Science and Technology
Örebro University
70182 Örebro, SWEDEN

Takao Terano

Chiba University of Commerce
Ichikawa, Chiba, 272-8512, JAPAN

Charles M. Macal

Decision and Infrastructure Sciences
Argonne National Laboratory
9700 S. Cass Ave.
Argonne, IL 60439, USA

ABSTRACT

During the World Café activity at the 2018 Winter Simulation Conference, we discussed Agent-based Simulation (ABS) credibility. The topic is important since credible ABS leads to an impact on society whereby ABS is implemented by users and they can benefit from it. This paper presents the perspective of three academic panelists and a practitioner on the credibility of ABS. The discussion reveals that the increasing use of ABS models to explain social phenomena or systems that exhibit emergent behavior pose a challenge for model credibility. Several points and suggestions are raised by the panelists, including evaluating ABS model credibility via its explanatory power, the multi-dimensionality of credibility and the role of software engineering approaches.

1 INTRODUCTION

In 2018, Margaret Loper, Sanjay Jain and Adelinde Uhrmacher introduced a new activity called the World Café to the Winter Simulation Conference. The objective of the World Café activity at the conference is to build a dialogue related to emerging or important topics in modeling and simulation. One of the topics was whether credible Agent-based Simulation (ABS) was an illusion or just a step away. Macal and Onggo facilitated the discussion. The discussion was very interesting and covered the perspectives of both academics and industry practitioners. During the discussion, it soon became clear that we did not have the same understanding as to what credibility in relation to ABS means. One thing the participants agreed on is that there is an overlap between validity and credibility, but they are two different concepts. Due to our differences, we did not manage to answer the main question of whether credible ABS is an illusion or just a step away. Hence, the main objective of this panel paper is to present an answer from the perspective of three ABS experts on the panel. Specifically, the panelists were asked the following questions:

- What is credibility in relation to ABS? Is it about the model? Is it about the modeling process? Is it about the people who are doing a study/project? Is it about the credibility of ABS as a simulation method or a scientific inquiry method?
- Based on the answer above, do you consider that there is a significant credibility crisis in relation to ABS and why? If the answer is yes, how do you think we can resolve this credibility crisis in relation to ABS?
- Is the availability of big data or any other recent developments in science and technology going to improve ABS's credibility, and if so why? Or is credible ABS just an illusion, and if so why?

The first panelist (Yilmaz) uses the lens of the ABS model as a generative explanation tool and argues that the credibility of an ABS model can be evaluated using its explanatory power. He then presents several evaluation criteria for the explanatory power of a model. The second panelist (Klügl) explains the reasons why developing a credible ABS model is particularly challenging. She further argues that big data alone may not contribute much to improving ABS's credibility. In contrast, she sees a potential contribution from software engineering approaches to improve the ABS model's credibility. Both panelists draw a parallel between the credibility of ABS and the credibility of Artificial Intelligence (AI). Inspired by Asura in Buddhism, the third panelist (Terano) discusses the plural faces of ABS and how these affect the efforts to make ABS models more credible. Following the statements from the panelists, this panel paper presents an interview with an ABS practitioner (Schumann) to get an industry perspective. He explains what people in industry usually do to improve the credibility of their ABS models. Finally, this paper concludes with a summary.

2 THE ROLE OF EXPLANATION IN EVALUATING AGENT-MODEL CREDIBILITY (YILMAZ)

Agent-based Models (ABMs) are successfully used in a wide range of application domains for a multitude of purposes, including behavior prediction and forecasting. However, the increasing role of ABMs as exploratory and explanatory instruments is raising concerns regarding the means for evaluating their credibility (Davis et al. 2018). Whereas computational agency provides an effective metaphor that brings realism through isomorphism between a system's observable characteristics and their conceptualization, the representation shifts toward complex interactions among the constituent elements, resulting in emergent behaviors that are sensitive to initial conditions and difficult to attribute to the elements of the system. Besides, application domains that involve social, cognitive and cultural behaviors posit additional difficulties in evaluating emergent behavior. What if the emergent behavior is not consistent with our expectations? Does it mean the model is not credible? Could it be the case that a simulation experiment generates new knowledge? When can we trust such new information?

2.1 Multi-Faceted and Explanatory Nature of Credibility Assessment

Due to the complex nature of human and social dynamics and a lack of data, as well as fragmented and narrow theories in such domains, the breadth and depth of predictive validation is severely limited. This appears to be analogous to a widely acknowledged crisis in the Artificial Intelligence domain that calls for credible and trustworthy explainable models, which can communicate their reasoning processes as well as how they reach conclusions for specific problems. To address these challenges, Explainable AI (XAI) (Gunning 2017) has recently become a notable area of inquiry to support the development of appropriate trust and reliance in autonomous systems. Similar concerns exist in the modeling and simulation domain, partly due to the significance of reproducibility and transparency in the use of models, as well as the need for trust in computational models when predictive validity is not feasible. In a recent report, Davis et al. (2018) recognize the need for a broader view of validity that needs to be assessed in accord with the objectives of a study. They propose a multi-faceted validation strategy that ranks a model's validity across multiple criteria, including model description, causal mechanisms, exploratory analysis, prediction and post-diction (i.e. retroactive explanation after the fact). Scientific problems, especially in the context of social and behavioral modeling, exhibit the inherent characteristics of Complex Adaptive Systems (CAS). Due to the impossibility of predicting CAS behavior, Davis et al. (2018) posit that it is necessary to apply model validation by leveraging relevant criteria across multiple dimensions. The report also highlights the increasingly common use of models as exploration tools for gaining insights into phenomena in the absence of theory and data. The use of such models is offered as an example to illustrate the limitations of conventional empirical similarity measures. As a result, a model's credibility is viewed not merely as the function of its features but also as acquired perception from the perspective and cognitive interest of a scientist in a given context of inquiry. These observations suggest the need for a better understanding of the processes, principles and methods used by scientists in instilling trust in models as they further their inquiries and gain experience. Such an understanding can then be used to characterize what makes models credible and to develop relevant computational strategies to bring transparency to the formation and growth (or decline) of credibility in light of specific objectives.

Building on the premise of XAI and recognizing the multi-faceted nature of validation, scientific explanation is one promising perspective that can provide a foundation for credibility assessments of models. ABMs are often developed to discover plausible explanations of scientific phenomena or to explore the consequences of assumptions. Similarly, the engineering of collective adaptive systems necessitates discerning decentralized, self-organizing coordination mechanisms that can produce and maintain a desirable systemic property. As ABMs increasingly serve as generative explanations (Epstein 2006), model credibility can be evaluated in terms of their explanatory power. Exploring the connection between credibility and explanation may very well open up new avenues for developing practical measures. That is, how good is an ABM as an explanation? Can we use the justificatory measures of explanations as metrics for evaluating their credibility?

2.2 Evaluation Criteria for Explanatory Models

Issues concerning explanation have long been a central focus of the philosophy of science, aiming to characterize normative aspects of causal reasoning. These studies have resulted in normative models of causal explanation, such as deductive (Hempel and Oppenheim 1948) and casual mechanical (Salmon 1984) accounts of explanation. On the other hand, psychological models of explanation focus on descriptive models of how humans engage in causal reasoning and sense-making to explain observations. By focusing on processes of explanation and the desirable characteristics of resultant explanatory models, we can characterize the evolving nature of model assessment through the lens of justification of explanations.

Explanatory models serve as plausible theories of a target phenomenon and its systemic properties. Philosophers of science and scientists have long considered the virtues of theories as a basis for choosing one theory over its rivals. The following is an overview of such criteria, which are classified into four categories: formal, pragmatic, presentation and evidential criteria.

1. **Formal Criteria**: Testability and internal coherence are fundamental formal characteristics of a desirable explanation. Testable explanatory models can be confirmed or falsified through experiments or empirical evidence. The internal coherence of an explanatory model requires that the explanation be coherent and avoid contradictory or incompatible statements.
2. **Pragmatic Criteria**: In practice, productive explanations open up avenues for the broadening and refinement of an explanation to increase its scope and level of detail. While such extensibility is critical, stability, as a measure of the compatibility of the new explanation to existing confirmed domain knowledge, helps to increase confidence in the explanation. That is, the explanation should retain established and firm explanatory constructs unless there is a compelling reason for significant separation from long-established knowledge.

3. **Presentation Criteria**: Simplicity and style (e.g. elegance) are two important characteristics regarding the form of explanations. Simplicity requires asserting only those features that are necessary to account for the targeted phenomenon. The style of the explanation should be elegant in terms of conciseness and precision.
4. **Evidential Criteria**: The empirical adequacy of an explanation measures the ability of the explanatory model to accommodate established evidence. External coherence or meaningful analogies to related theories in similar and relevant domains provide support for plausibility and the eventual acceptability of an explanation. Moreover, a preferred explanation should be general enough to be applicable to more targeted phenomena than its rivals. Also, a successful explanation can provide a generic schema to unify diverse phenomena by characterizing them as concrete instances of its schematic explanatory model.

The generation of explanatory models with such traits involves the interplay of multiple activities and is a highly dynamic process involving specific inferential processes.

2.3 Evaluation Criteria for Explanatory Models

Explanation is an iterative, incremental process. The provision of a model-based explanation stimulates further inquiry to deepen and broaden the scope of plausible explanations. Initial explanations often provide a template to continue the search process, allowing model-builders to iteratively refine the model's causal mechanisms by adding details to increase its level of resolution. During the process, the focus of inquiry can shift as a result of the evaluation of alternative explanatory mechanisms to make inferences regarding the best explanation. Explanation is also a symbiotic adaptive process, because as the process of justifying an explanation unfolds, a symbiotic search process takes place between the hypothesis (e.g. model structure) and the experimental space. Following a search within the structural space of models, experimental conditions are created in such a way that they provide new emergent information that would otherwise be unavailable.

Emergent behavior is a property of the overall system and indicates a trait not possessed by any one of the constituent components of the system. Emergent behavior can be unexpected and surprising, as it may be an indicator of new knowledge that cannot simply be inferred as a linear function of agent attributes. The recognition of such emergent behavior prompts the need for an explanation to give an account in terms of causal mechanisms that are responsible for the observed behavior. Having an introspective capability to assess the consequences as well as the premises of one's own behavior is critical for reflection. Explanation requires the ability to reflect on the underlying causes of observed emergent behavior. Such reflection enables the explanation of behavior in terms of assumptions and objectives that drive observable outcomes. A model that is provided with such self-awareness capabilities can compare its simulated behavior to expected regularities and evolve an understanding of its own features and how they contribute to the desired behavior. In the early stages of model-based experimentation, there is minimal self-awareness in the form of a set of features. As experiments are conducted, features compete and are evaluated in terms of their degree of contribution to desirable or undesirable states. The ability to communicate to end users such self-awareness metamodels can help models acquire credibility over the course of their use.

3 CREDIBILITY AND THE ROLE OF PROPER ENGINEERING (KLÜGL)

3.1 Credibility?

As introduced above, credibility is not as obvious a notion as one might expect. The term itself is explained by the Merriam Webster Dictionary as "capacity for belief". Only a model with minimum validity can provide that capacity. Credibility – as a more subjective quality compared to validity – determines whether a developer, user or stakeholder of a simulation model eventually trusts the results and statements produced. Many elements contribute to the establishment of this trust, mainly overall systematicity of the study approach, transparency and clearness of the model and simulation, and explainability of the simulation results. In cases in which the phenomenon under study is mostly theoretical, the model is consequently very abstract, so that classical validation is not possible, though credibility may nevertheless be established.

Doubts can be cast on credibility by minor aspects, despite everything apparently having been done to assure credibility. In an interdisciplinary project many years ago, we developed a model for the reproductive decisions of insects that may lead to sociality. The model focused on the core elements, so it was quite abstract. Model and simulation results were thoroughly analyzed. However, the biological partner never trusted the results produced since, due to the way we implemented virtual parallelism based on a random shuffle, there were (minor) signs of stochasticity which did not influence the result, but “appeared weird” to the eyes of the domain expert. In the end, this project could be seen as having failed, as without trust in the results, the biological expert never actually used them.

A related concept is believability, which can be seen as how convincing simulation results are. The term mostly relates to how realistic or conforming to expectations the behavior of simulated (virtual) agents is. Believability is often established based on Face Validation.

3.2 What Makes Agent-based Modeling Special?

Starting from the idea that the credibility of simulation models can be established in general, the question arises of why we are discussing credibility specifically for agent-based modeling and simulation. Why would one ever doubt that the credibility of an agent-based simulation model can be established in a way that is different to other approaches?

3.2.1 ABS in the Social Sciences

One of the main application areas of agent-based modeling and simulation is social-science simulation. One can observe that highly abstract models often appear to be oversimplified, despite those constructing them having a thorough grounding in social theory. In the early days of Agent-based Simulation models in the social sciences, the KISS principle was pursued to the extreme, damaging the credibility of a general approach (Edmonds and Moss 2004). At first, modeling and simulation were done by people without formal education in engineering, and teaching modeling and simulation was seen as equal to teaching programming. Validation was seen as an impossible endeavour. Since the early 2000s, this has clearly changed based on works like that of Richiardi et al. (2006), massively promoting the systematic development and analysis of agent-based simulation models and experiments. The establishment of the CoMSES network (https://www.comses.net/), with the OpenABM platform, was a big step towards the credibility of an agent-based simulation approach in the social (and ecological) sciences. Nevertheless, the area appears to still – wrongly – struggle with a reputation of lacking modeling and simulation professionalism.

3.2.2 Complexity, Non-Linearity, Emergence

Agent-based simulation models exhibit a number of properties which make them particularly attractive for a number of application domains. An agent-based simulation has at least two levels of aggregation: the agent level and the society level. Those levels are connected during simulation – behavior and interaction on the agent level generate phenomena observable on the society level. Norms and structures emerging on the society level influence the agent behavior on the lower level. Relations between the levels are implicit and encoded into individual agent representations and programs. Agent behavior does not simply add up, but enables capturing complex, non-linear phenomena, such as emergence. This results in an inherent brittleness of simulation results. Agent-based simulation models are complex and not easily presentable as a whole in any transparent way. Validation, testing and explanations are thus challenging, as they need to be done on both the agent and society levels (Klügl 2008), while appropriate data for all the aggregation levels are often not available. If a model is not to be developed in vain, then the credibility of the model, as well as the simulation results it produces, can and must be established, even if it is challenging and effortful to do so. This is the price to be paid for the increased expressiveness of the modeling and simulation paradigm.

3.2.3 Missing Established Formal Grounding

While other modeling approaches and simulation methods have an established formal basis that may support the development of specification languages and formal analysis tools, agent-based modeling and simulation lacks that. There is nothing comparable to Differential Equations for Continuous Models, DEVS for Object-Oriented Modelling or Queueing Systems, Petri Nets, etc. that would work for all agent-based simulation models, formal grounding is specific for a domain. The result is that models sometimes appear to be rather arbitrary. Constraints on modeling and simulation stem from what can be formulated in a programming language; so, actually, there is no limit in what can be integrated into an agent model. There is currently no shared way of resorting to or justifying modeling decisions based on an underlying theoretical framework. There have been attempts at formalizing (Klügl and Davidson 2013), yet neither were they comprehensive, nor could they establish the missing grounding in the community.

A consequence of this missing formal grounding is also that tools for developing agent-based simulation models often resort to programming in a universal programming language, mainly framing the program and providing access to suitable libraries. Depending on the programming skills of the modeler/ developer, models are more or less clean and understandable, and use more or less abstract programming language constructs. The program implementing a simulation model may appear as a black box for stakeholders without sufficient programming skills. If the results are not fully explainable by documented model features, credibility suffers massively. An interesting approach comes from software engineering with (software) model-driven development providing a systematic model refinement and representation approach resulting in a runnable simulation, e.g. as done in Santos et al. (2018).

3.3 Is There a Crisis of Credibility?

One of the questions to be discussed is whether there is a significant crisis in the credibility of ABS. My answer is that there should be no problem with the credibility of an agent-based simulation model if proper systematic model engineering and development is done, which means thorough results analysis, including the generation of explanations, especially for surprising outcomes, as well as thorough model verification and validation as well as understandable result discussion. A modeler must work in a professional way. If modeling and simulation studies end up with results of limited credibility, the problem is a failure to invest sufficiently in necessary activities. What is missing are tools that make the production of documents and explanations, as well as testing frameworks, convenient and fast to use.

3.4 Big Data, Agent Learning – Advancing Agent-based Simulation towards More Credibility?

During the last few years, new approaches have been published showing the successful replacement of traditional expert-based model development by machine-learning techniques based on (deep) reinforcement learning or deep neural networks. Prominent examples can be found in traffic-related areas. An example is learning to predict location choice – which traditionally forms an element of travel-demand modeling – based on massive point path data captured from mobile phones (Kong and Wu 2018).

However, without proper engineering of assumptions hidden in data sets and in the configuration of the networks used, as well as full analysis and explanation of generated phenomena, the learnt model is again a black box. In the context of model credibility, being forced to take the results as given is highly counterproductive. In Artificial Intelligence (AI), a similar credibility crisis has been identified, leading to a move towards so-called "Explainable AI" striving for transparency and human understandability of automated intelligent reasoning systems, no matter whether based on deep networks and machine learning or more traditional AI approaches (Adadi and Berrera 2018). During the last years, techniques have been suggested that are similar to the (simulation) model and result analysis portfolio including meta-modelling. For example, Ribeiro et al. (2016) introduce an approach for generating local, interpretable approximations of learnt black-box classifiers based on small variations of the input. Biecek (2018) introduces a R-based package of several (learnt) model analysis tools.

The term "Explainable AI" actually was originally coined in the area of Neuro-Symbolic Integration which proposes logic-based reasoning for supporting of the learning process as well as providing explanations about the results generated by the neural/deep network. A survey can be found in Besold et al. (2018). It could be interesting to observe the advances in this area and transfer tools and approaches developed to explain the reasoning behind decisions made by an Artificial Intelligence System to generate explanations of why an (agent-based) simulation model produced a particular simulated system trajectory or particular simulated phenomena.

4 PLURAL FACES OF AGENT-BASED MODELING (TERANO)

4.1 Asura and Agent-based Modeling

An asura in Buddhism is a demigod or titan who has plural faces (Fig. 1). Similar to Asura, the credibility of new scientific principles is determined by long-term plural discussions. In this section, I would like to present my ideas on the plural faces of agent-based modeling (cf. Kurahashi et al. (2018) and Koch et al. (2019)).

Figure 1: Asura Statue in Buddhism.

An agent is an entity that has an internal state and decision-making and communication functions. Agents can model humans, organizations or even objects, such as molecules. Through the micro-interactions of agents, a macro-scale order with bottom-up effects emerges. From the standpoint of creating models via which to view the world, we cannot view micro-scale conditions in detail. Therefore, academia has advanced to the point of observing macro-scale phenomena and creating models involving macro-scale variables. Because agents have internal states and communication functions, they can observe the macro-scale order. As a result, top-down influences from the macro-scale are transmitted to the micro-level, where they alter agent behavior. This is the complex behavior that is generally seen in social phenomena. Once micro-scale agents begin to observe macro-scale phenomena, complex interactions that form micro-macro links arise (Fig. 2).

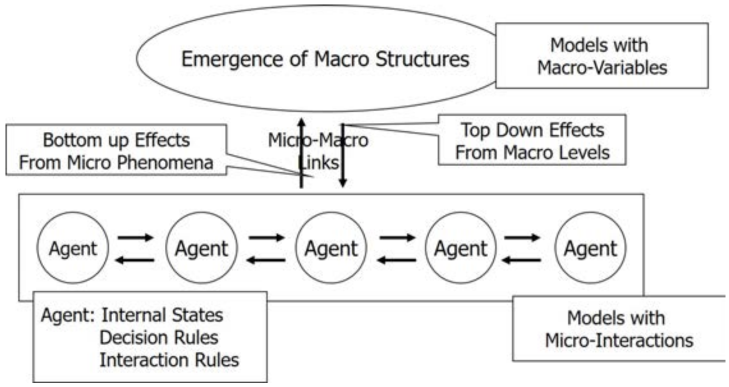

Figure 2: Framework of Agent-based Modeling.

The plural faces of agent-based modeling include i) theoretical and real world issues, ii) differences between technical and social time scales, and iii) validation and accreditation issues.

4.2 Theory vs Real World Issues

Any agent-based models are easy to implement as computer programs; however, they usually consider models as lacking of grounding theories. Actually, in the traditional social and mathematical sciences, there usually exist grounding theories. For example, to analyze financial market behaviors, they should refer to recent theoretical results in not only Economics and/or Game theory, but also Econo-physics theories. Under the simplest assumption simulations, we are able to get the same results as existing theories; that is to say, existing theories will support the credibility of an agent-based model. But, in order to be convincing, simulation results in general are not enough. This is because we may employ many assumptions in our models. As a result, the collective behaviors of agents in a model become hard to explain without concrete examples in the real world. With agent-based models, we can bridge existing theories and the real world. In other words, agent-based modeling is a middle way between theory and the real world. Thus, it is worth studying.

4.3 Technical vs Social Time Scale

In the engineering of agent-based modeling, new techniques related to artificial intelligence always emerge and older ones are usually re-invented several times. The life time of computer programs with cutting-edge technologies might be a decade, if they are the most advanced ones. Hence, the time scale is relatively short. On the other hand, in natural science fields, theories are true until new measurement methods are invented. A good theory has a relatively long time scale. To take examples from physical science, Newton's Laws remain true for a long time. After new suitable measurement devices were invented, Einstein's ideas were then fully accepted. Our social life and concepts is somewhere in between short and long time scales; they should continue for at least one to ten centuries. For example, people before the Renaissance period could not understand financial or accounting theories, which are now good and challenging fields for Agent-based Modeling. In the social-science context, they emphasize the importance of the historical continuity of theories. Our agent-based models must cope with such different time scales. In our experience, one of our research topics focuses on archaeological and historical issues in ancient Japan and China. To carry out such simulation studies, we must use both cutting-edge optimization techniques and historical records coming from various documents. This causes difficulty for the credibility of the model and results.

4.4 Validation vs Accreditation

As with any computer program, agent-based simulation programs always face with verification, validation and testing issues. Although they are difficult to solve, the issues should be treated as software engineering problems. However, because of the intrinsic stochastic properties of agent-based modeling, simulation results usually differ from each other in each run. For this reason, in the traditional simulation literature, such as operations research, statistical testing techniques are usually employed to give convincing results. On the other hand, I believe that a real-world event we target with agent-based modeling is only one instance of could-be-events, which might or could occur. Thus, we should not only rely on statistical techniques. Fortunately, with the recent advances in so-called big-data technologies, we are able to handle vast numbers of agent simulation logs; yet, the simulation results are virtually generated, not real, big data. For example, we are able to analyze the complex behaviors of interbank agents in bankruptcy in the financial domain with standard big-data analysis techniques. Thus, I think a combination of agent-based models and big data analysis is promising. However, the accreditation of models could be another problem. In recent behavioral modeling and simulation conferences, such as Zacharias (2008), they require models with both VV&T and accreditation activities. In this sense, we have not been successful in conveying the credibility of agent-models to ordinary audiences.

4.5 Concluding Remarks

In this section, I have discussed the plural faces of agent-based models to convince the reader of their credibility. They say that the faces of an asura reflect the mental state of a human being obsessed with ego, force and violence. The agent-based models we are developing always look for good interpretations of social phenomena and/or social systems, although they are not sufficient to model all the states of human beings and societies. However, I believe that agent-based modeling is a promising way to both understand and design next-generation societies. It took over one century for statistical techniques to achieve acceptance in the scientific literature in our societies. Compared with this, agent-based modeling is too young to get accreditation. Going back to the original question of the panel discussion, my answer is that credible agent-based simulation neither an illusion nor one step away, but rather that it will likely take a long time for agent-based modeling to become credible to a large community of scientists. We must continue to struggle for credible positions in the scientific literature.

5 ABS CREDIBILIBTY IN INDUSTRY: AN INTERVIEW WITH BENJAMIN SCHUMANN

To complement the views of academics, Onggo conducted an interview with Benjamin Schumann, a simulation consultant who has done several projects using ABS (https://www.benjamin-schumann.com/). He is well-known among ABS practitioners and regularly blogs about ABS. The summary of the interview is as follows.

According to him, from an industrial perspective, a credible ABS model is a model that is trusted by its users. The most accurate model will not be used if the users do not trust it. Trust comes from understanding. This is informed by various aspects:

- **Training and Development**: the modeler should ideally build the model together with the end user. Often, this is not possible. However, close collaboration, reviews and discussions can build trust.
- **Traceability**: Industrial models are typically fairly complex. Users must be enabled to trace certain behaviors. If an agent behaves "oddly", users must be able to click on it to learn more about its current state. Ideally, they should be able to navigate throughout the entire model in order to find the root cause for the behavior in question.
- **Explainability**: Often, users run the model and ask themselves, "Why is X happening?" To inspire trust, the model should feature substantial help functionality, ideally dynamically, as part of the

model. A simple "help" button can explain typical issues for a specific situation. The power of simulations allows showing context-sensitive help and explanations. Despite the additional workload to set these up, it is a worthy undertaking.

It is interesting that he makes the point that the most accurate model (or even a valid model) will not be used if the users do not trust it (i.e. lack of credibility). He clearly differentiates the terms model accuracy and a more subjective measure of model credibility. This is similar to Klügl, as she clearly differentiates model validity, model believability and model credibility. Another interesting point is that he mentions that trust comes from understanding. This statement resonates well with Yilmaz's statement on the relationship between the explanatory power of an ABS model and its credibility. Klügl also highlights that it is important that users can understand a model and simulation results can be explained. Finally, Schumann also confirms the importance of working together with the end user (i.e. increase the face validity of the model). He underlines the importance of traceability, which is an important feature of an explanatory model. As mentioned earlier by Terano, an ABS model can produce massive data, which not only supports traceability but also opens up an opportunity to use big-data analytics to find patterns in simulation output data.

On the question of the ABS credibility crisis whereby users do not trust the model, leading to it not being used, he suggests several ways to prevent a credibility crisis happening; for example, follow best practices (e.g. use software engineering approaches as discussed by Klügl and Terano), embed the model into a web of support (e.g. videos, offline documentation etc.), train users to train future users, and train users to amend models for changes in the real system (avoid outdated models). His comment on offline documentation resonates with the panelists' statements about the importance of documentation (Klügl) and reproducibility and transparency (Yilmaz) to support model credibility. Monks et al. (2019) discussed the reproducibility and transparency issues in simulation studies. They reviewed several documentation guidelines that have been proposed to promote reproducibility and transparency. They also propose guidelines that cover Discrete-event Simulation, System Dynamics and Agent-based Simulation. Initiatives such as OpenABM platform (https://www.comses.net/), also promote the reproducibility and transparency of agent-based models. Finally, Schumann strongly believes that by building models together with end clients, ensuring full traceability, and adding a lot of dynamic/ interactive explanations to the model, lays the foundation for a credible model.

6 SUMMARY

The panelists agree that credibility in ABS is multi-dimensional and more subjective than model validity. They have argued that building a credible ABS model is challenging, especially when it is used to explain social phenomena. Given that ABS has increasingly been used as a tool to explain social phenomena or systems with emergent behaviors, the credibility of an ABS model can be evaluated from its explanatory power. From the perspective of industry, the credibility of an ABS model determines whether users will trust and use the model. Trust comes from understanding and the ability to explain simulation outputs. The panelists drew a similarity between the credibility issue in ABS and explainable Artificial Intelligence (XAI). From the panelist's statements, we can infer that credible ABS is not an illusion because we have made some progress in research to improve the credibility of ABS. However, more research needs to be done in this area; hence, credible ABS is not just a step away.

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AUTHOR BIOGRAPHIES

BHAKTI STEPHAN ONGGO is an Associate Professor of Business Analytics at Southampton Business School, the University of Southampton. He is a member of the Centre of Operational Research, Management Sciences and Information Systems (CORMSIS). His research interests lie in the areas of simulation modeling methodology (symbiotic simulation, hybrid modeling, agent-based simulation, discrete-event simulation) with applications in operations and supply chain management and health care. He is the associate editor for the Journal of Simulation and the chair of The OR Societys Simulation SIG. His website is https://bsonggo.wordpress.com. His email address is b.s.s.onggo@soton.ac.uk.

LEVENT YILMAZ Professor of Computer Science and Software Engineering at Auburn University with a joint appointment in Industrial and Systems Engineering. He holds M.S. and Ph.D. degrees in Computer Science from Virginia Tech. His research interests are in agent-directed simulation, cognitive computing,and model-driven science and engineering for complex adaptive systems. He is the founding organizer and general chair of the Agent–Directed Simulation Conference series. His email address is yilmaz@auburn.edu.

FRANZISKA KLÜGL is is a Full Professor in Information Technology at the Orebro University (Sweden). She is member of AASS research center. She holds an Habilitation and PhD in Computer Science from the University of Wurzburg, Germany. Her main research interests are related to questions on model and simulation engineering especially for multi-agent systems. Her email address is fkluegl@acm.org.

TAKAO TERANO is a Professor at Chiba University of Commerce (Japan) and an Emeritus Professor in the Department of Computer Science, School of Computing, Tokyo Institute of Technology. He had the Doctor of Engineering Degree in 1991 from Tokyo Institute of Technology. His research interests include Genetic Algorithm-based Machine learning, Case-based Reasoning, Analogical Reasoning, Distributed Artificial Intelligence, Cooperative Agents, Computational Organization Theory, and Knowledge System Development Methodology. His email address is terano@cuc.ac.jp.

CHARLES M. MACAL is the Group Leader of the Social and Behavioral Systems Group in the Systems Science Center of the Global Security Sciences Division at Argonne National Laboratory. He has a PhD in Industrial Engineering & Management Sciences from Northwestern University and a Master's Degree in Industrial Engineering from Purdue University. His email address is macal@anl.gov.