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EDITORIAL

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Using Simulation in Information Systems Research

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Abstract

Like all other scientific research methodologies, simulation has its strengths and limitations. When used properly, simulation can be a powerful tool for developing new theoretical insights into IS phenomena of interest. Although simulation methods are not new in the IS field, there has been no systematic discussion about which simulation methods are suitable for IS research, when simulation is the most appropriate methodological choice for IS research, and how to evaluate simulation research. In this editorial, I provide an overview of simulation methods that may be used in IS research and discuss how they are typically used. More importantly, I provide guidelines for IS researchers on how to choose simulation among alternative methodologies and highlight six key criteria for evaluating simulation research. Overall, this editorial can provide useful guidance to IS researchers, editors, and reviewers when choosing, conducting, and assessing simulation research.

Keywords: Simulation, Agent-Based Modeling, Fitness Landscape Modeling, System Dynamics Modeling, Research Methodology, Information Systems Research

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1 Introduction

Simulation is a scientific research methodology that is widely used in the natural sciences (e.g., physics, chemistry, and biology) and the social sciences (e.g., economics, management, and sociology). Like other methodologies, simulation has inherent strengths and limitations; when used properly, it can serve as a powerful tool offering novel and unique theoretical insights into IS phenomena of interest (Dong, 2019). This is particularly the case when studying phenomena that involve "multiple and interacting processes, time delays, or other nonlinear effects such as feedback loops and thresholds" (Davis et al., 2007, p. 483). Researchers often find it difficult to handle such complexity with analytical or empirical methodologies based on a quantitative tradition, because mathematical or quantitative analysis for processes with a complex, nonlinear nature can be extremely challenging (Hannah et al., 2021; Harrison et al., 2007). While the qualitative tradition provides an alternative way for exploring complex, process-oriented theoretical insights, it also has its limitations in terms of precision and the generalizability of the findings.

Simulation is a methodology that essentially combines analytical modeling and quantitative analysis by developing a computer algorithm that models a phenomenon of interest in stochastic processes, which generate data for quantitative analysis. Thus, simulation modeling does not require strict assumptions for tractable mathematical solutions as analytical modeling often does (Hannah et al., 2021). Simulation applies experimental design when running computer algorithms, similar to empirical study with experiments. In this sense, simulation can leverage strengths from analytical and empirical methodologies and once computational models are properly developed, complex phenomena can be investigated with rich data output in controlled settings to examine causal effects. Since simulation can unveil multiple and interacting processes across different levels over time, researchers can use it to investigate the underlying theoretical mechanisms and advance theory. Therefore, simulation is widely considered to be a powerful tool for *theory development* (Davis et al., 2007).

Simulation has been used by IS researchers for years. Taking four premier journals in the IS field as examples, Figure 1 shows the numbers of articles related to simulation that were published in *Information Systems Research* (ISR), *Journal of the Association for Information Systems* (JAIS), *Journal of Management Information Systems* (JMIS), and *MIS Quarterly* (MISQ) over the past decade (2011-2020). These articles were identified through an abstract search using the keyword "simulation" in the EBSCOhost database. The selection of journals is obviously not comprehensive; the motivation is simply to showcase the trend of simulation papers in some leading IS journals. As Figure 1 shows, there has been a steady interest in simulation over the years, but simulation still represents a less common methodological choice. ISR has led the increase in using simulation and, recently, MISQ published five articles in a special issue on complexity and IS research, of which three used simulation methods, indicating the strengths of simulation in researching complex IS phenomena (Benbya et al., 2020). Therefore, simulation is a relatively understudied but useful research methodology, especially given the increasing complexity of IS phenomena (e.g., digital platforms and ecosystems).

The shortage of methodological guidance, among other reasons, may contribute to the underutilization of simulation in IS research. There are methodological articles guiding the choice, use, and assessment of simulation work in other disciplines such as management (e.g., Davis et al., 2007; Harrison et al., 2007), whereas discussion on simulation methods is scarce in the IS field. What simulation methods may be used in IS research, when to choose simulation, and how to evaluate simulation research are important questions that have not yet been systematically discussed in the field. To encourage and support simulation IS research, this editorial aims to fill this gap by (1) explaining the main simulation methods and procedures that may be used in IS research, (2) discussing when simulation is the most appropriate methodology to use for IS research, and (3) proposing key criteria to guide editorial and review processes when evaluating simulation research.

2 Simulation Methods for IS Research

Next, I provide an overview of the main simulation methods that may be used for IS research and how they are typically applied. Given the absence of a standard typology of simulation methods, I categorize these simulation methods into three modeling approaches: (1) *agent-based modeling*, (2) *fitness landscape modeling*, and (3) *system dynamics modeling*. These categories of modeling approaches are by no means comprehensive but summarize the simulation methods that are particularly useful to model "systems" that are fundamental in IS research (Nevo & Wade, 2010; Rai et al., 2022). Other methods, such as Monte Carlo simulation in economic or methodological research and discrete event simulation in operations research, are not central to modeling "systems" and are therefore excluded for the purpose of this editorial.

Agent-based modeling. I use agent-based modeling as a broad category that contains many specific modeling approaches with distinct foci on the adaptation of agent behaviors, collective patterns of agent behaviors, and probabilistic processes of agent behaviors (Davis et al., 2017; Garcia, 2005). Generally speaking, agent-based modeling simulates the actions and interactions of autonomous agents (e.g., individuals or organizations) to understand the behaviors of a system at the collective level and what governs its outcomes (Macel & North, 2010). Specifically, it models simultaneous decisions and interactions of multiple agents to explore the emergence of complexity, as the whole system could be different from the sum of its parts. The agents are often characterized as boundedly rational and follow simple decision rules and heuristics that are adaptive, allowing experiential learning over time. Agent-based modeling is particularly powerful for uncovering the processes through which system properties emerge from the interactions of agents. It is probably the most widely used simulation method by IS researchers to investigate a variety of topics, such as the impacts of technological choices on network-wide standardization (Weizel et al., 2006), the role of information technology (IT) in organizational learning (Kane & Alavi, 2007), digital competition for online advertising (Chang et al., 2010), IT use processes (Nan, 2011), the evolution of IS infrastructure (Haki et al., 2020), search matching for recommender systems (Malgonde et al., 2020), the dynamics of recommender systems (Zhang et al., 2020), technological choices with different organizational aspirations (Dong, 2021), and effective coordination of human and machine learning (Sturm et al., 2021).

Fitness landscape modeling. Fitness landscape modeling was originally developed and used by evolutionary biologists to study how rapidly and effectively a modular system consisting of interactive components adapts to reach better fitness in natural selection processes (Kauffman, 1993). This method was later used to study the complexity of a system such as an organization or a product (Levinthal, 1997). In fitness landscape modeling, there are only two primary parameters N and K in the model; thus, this method is also referred to as *NK* modeling. N denotes the number of components in the system, and $0 \leq K \leq N - 1$ indicates the interdependence among these components.

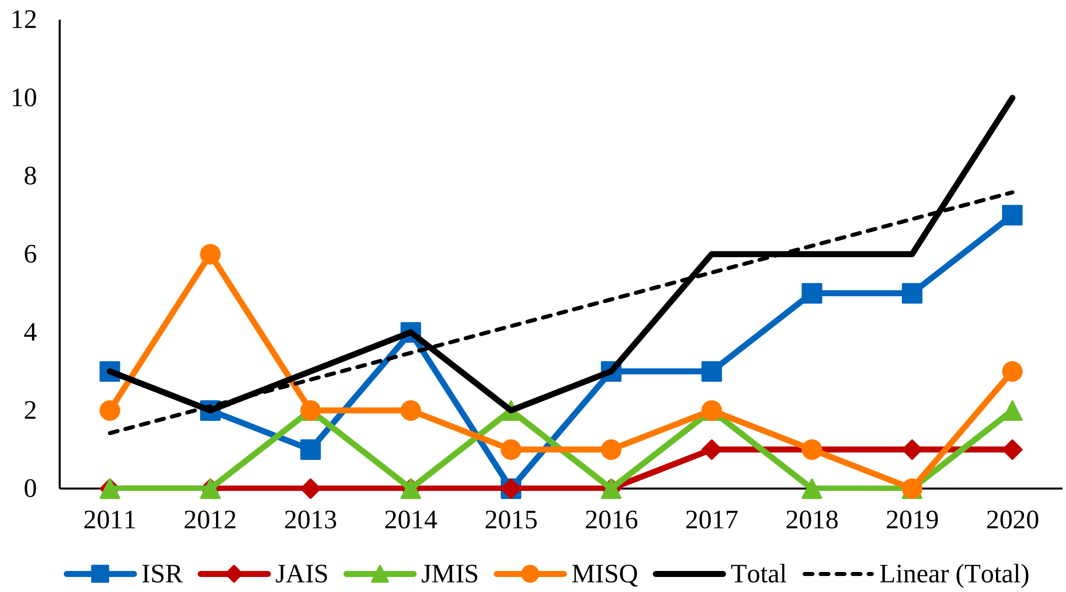

Figure 1. Publications Related to Simulation in Premier IS Journals

Therefore, a larger *N* indicates a larger system, whereas a higher *K* means that the fitness of a component is more dependent on other components in terms of fitness. The fitness landscape is simulated by assigning fitness values to every possible combination of values for *N* and *K*. When *K* is smaller, the fitness landscape is smoother with fewer optimal combinations (one or a few peaks, if visualized); as *K* increases, the fitness landscape becomes more rugged (many peaks with varying heights), making it much more difficult to determine the optimal combination. Thus, fitness landscape modeling is useful for exploring the speed and effectiveness of specific search strategies to improve performance in the adaption of a system on a fitness landscape. It has particular strengths for understanding how the adaptation of complex systems is influenced by the interactions among components. Fitness landscape modeling has been widely used in other disciplines such as management (e.g., Lee et al., 2010; Levinthal, 1997), but is relatively underutilized in IS research (Benbya et al., 2020). Until recently, Nan and Tanriverdi (2017) employed fitness landscape modeling to study the role of IT in hyperturbulence, which encodes sustainable competitive advantage of firms stemming from their IT-based strategic actions. Brunswicker et al. (2019) applied fitness landscape modeling to explore the decoupled architecture of two-sided platforms and its performance impacts in relation to app producers' design strategies. Hahn and Lee (2021) used fitness landscape modeling to investigate the complex impacts of cross-domain knowledge in IS development.

System dynamics modeling. System dynamics modeling focuses on how the causal relationships among parameters influence system behaviors (Sterman et al., 1997). To this end, system dynamics modeling simulates a system (e.g., an organization or a market) as a series of processes with circular causality, assuming that these processes have some common parameters allowing them to intersect in complex causal loops. Typical parameters used in system dynamics modeling fall into two groups: *stocks* that accumulate and dissipate over time, and *flows* that specify temporal rates in the system. System dynamics modeling is particularly powerful for understanding casual complexity with multiple loops. Rahmandad and Sterman (2008) compared system dynamics modeling and agent-based modeling and discussed their relative advantages and disadvantages. As a notable example, Amitava and Rahul (2005) used system dynamics modeling to demonstrate the dynamic behaviors of IT offshoring between two countries. Fang et al. (2018) provided a useful overview of how system dynamics modeling could be used in IS research and showcased its application in the context of e-commence to understand resource endowment and firm performance. More recently, Pentland et al. (2020) developed a model to simulate the dynamics of process changes supported by digital technologies, which could be viewed as a novel employment of system dynamics modeling.

While the above modeling approaches and the foci of these simulation methods are distinct, their research procedures are comparable. Figure 2 shows a flowchart of typical procedures undertaken in simulation research. Simulation studies often start with developing a computational model, which entails key features abstracted from the objects of analysis based on certain assumptions. These key features are modeled as parameters defined by certain distributions, and the relationships among these parameters constitute the model that could be computed to examine the changing values of some parameters with input from the values of other parameters. The next step is programming the computational model into a computer algorithm using pre-equipped simulation packages or coding it from scratch. The algorithm allows the computer to compute the model with input from different parameterizations that researchers wish to manipulate in an experiment. Then, simulation experiments can be designed and conducted by running the computer algorithm under different conditions defined by manipulated parameterizations while holding all other conditions equal. After that, data output can be analyzed statistically or visually. Finally, it is important to interpret the simulation results meaningfully to generate new theoretical insights into the phenomena of interest. This is a key step for theory development in a simulation study (Lave & March, 1975).

3 Choosing Simulation for IS Research

While IS researchers have a steady interest in simulation, it is not a common methodological choice in the IS field. Offering some guidelines for choosing simulation among alternative methodologies could be useful to encourage the choice of simulation when appropriate. Next, I discuss some important aspects when considering simulation as a methodological choice for IS research, including (1) *suitability of research questions*, (2) *availability and quality of empirical data*, and (3) *complementarity with other methodologies*.

Suitability of research questions. A key advantage of simulation relative to other methodologies is that it is powerful for uncovering complex causal loops because of massive interactions within and across different levels over time (Davis et al., 2007). If the research questions are complex, involving interactive patterns, temporal variations, cross-level influences, and causal complexity, simulation could be more suitable to answer these questions. IS researchers are often interested in complex sociotechnical systems that consist of technology and human activities in organizational contexts, which have enduring and lagged influences on each other. Depending on the specific perspective that IS researchers hold, IT and organizational factors may have complex causality that is technology driven (i.e., technological imperative), organization driven (i.e., organizational imperative), or dual constructive (i.e., emergent perspective), across micro-, macro- and mixed levels (Markus & Robey, 1988; Markus & Rowe, 2018). For example, Nan and Tanriverdi (2017) used simulation to explore the cross-level nonlinear causality between firm-level IT-based strategic actions and collective-level IT-induced hyperturbulence. Such cross-level nonlinear causality is very difficult if not impossible to tackle using empirical methods, making simulation a particularly suitable methodological choice. In this case, simulation can generate clean data and allow insightful causal analysis. Most simulation research is conducted with experimental design, allowing for rigorous tests of causality.

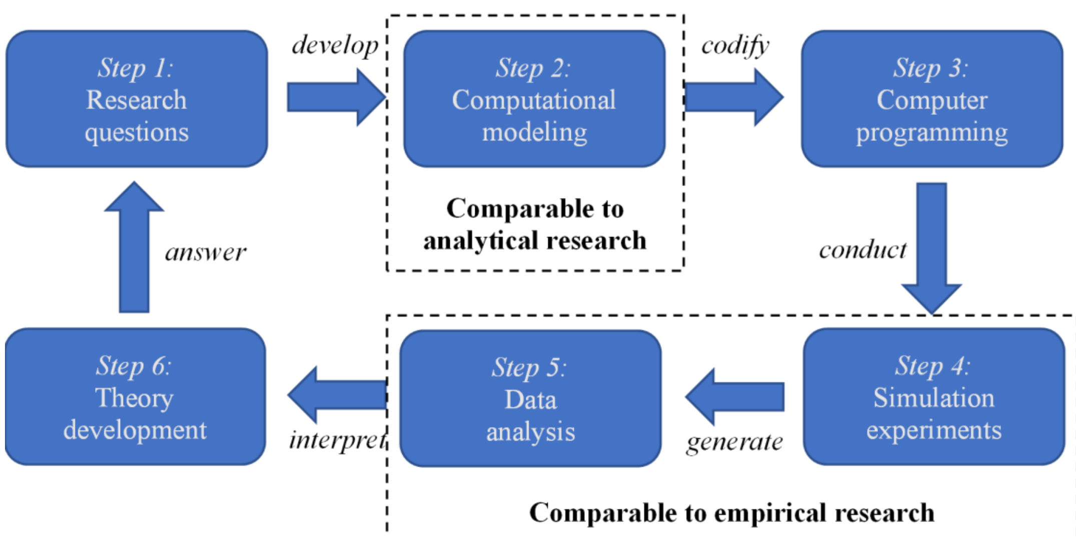

Figure 2. Typical Procedures of Simulation Research

Also, simulation can demonstrate emerging patterns at the macrolevel via bottom-up processes based on individual decisions and interactions at the microlevel and can thus offer deep insights into the theoretical mechanisms underlying these processes.When such microlevel data are required and unavailable to IS researchers, simulation is particularly suitable for answering research questions. For example, in support of empirical analysis Dong (2021) studied the performance and risk of technological choices with different organizational aspirations when the manager’s aspiration type in each firm used in goal setting was not observable over time. In this case, simulation can be used to advance theory.

Complementarity with other methodologies. Simulation methods could also be combined with analytical or empirical methods, providing unique opportunities for IS researchers to address the limitations of a single method. There has been a long tradition of diverse methods in the IS field, and such complementarity of simulation with other methodologies can therefore empower this tradition. For instance, analytical modeling can help develop computational models for simulation; analytical modeling can also be combined with numerical analysis with simulation when the analytical model does not generate closed-form solutions (Hannah et al., 2021). Simulation can also be combined with empirical methods to validate assumptions or test propositions (Dong, 2019); empirical studies can use simulation methods to investigate the theoretical mechanisms underlying empirical findings of certain causal relationships or processes (Volmar & Eisenhardt, 2020). A multimethod approach combining simulation and other methodologies can allow IS researchers to leverage mutually reinforcing strengths from different methods. For example, Park et al. (2012) proposed a relational inference model to determine the accuracy of self-administered consumer profiles and conducted an empirical validation for the model. To further examine the robustness of results, they combined empirical analysis with several simulation experiments, which helped to considerably strengthen the evidence.

4 Evaluating Simulation Research

To assess the quality of simulation research, the following criteria could be used as the basis of evaluation, in terms of the choice of simulation (Criterion 1), the “input” of simulation (e.g., assumptions, modeling, and research design) (Criteria 2-4), and the “output” of simulation (e.g., results, and theoretical insights) (Criteria 5-6). These criteria aim to provide an overview of the key aspects of assessment for those who are less familiar with simulation research. Next, each criterion will be discussed in terms of some tangible guiding questions, as summarized in Table 1.

Criterion #1: Appropriateness of using simulation. Related to the earlier discussion, the first criterion for evaluating a simulation work would be assessing the choice of simulation as the research methodology. Is simulation an appropriate methodology to answer the research questions? How suitable is the chosen modeling approach? More importantly, does simulation offer unique theoretical insights into the phenomena of interest or can it be replaced by alternative methodologies? If the phenomena do not involve sufficient complexity or could be more readily researched using alternative methodologies, the choice of simulation is questionable. Another practical issue is that simulation studies often impose a heavier cognitive load on editors and reviewers, as significant amounts of effort need to be invested in digesting the integrative details of the model, data analysis, and theory development. If simulation does not offer unique theoretical insights, the return on investment (ROI) of using simulation might be lower than the ROI of using other methodologies.

Criterion #2: Reasonableness and generalizability of assumptions. Simulation relies on mathematics to develop computational models. Like analytical models, computational models need to make specific assumptions regarding what key factors should or should not be considered and how they relate to each other in the modeling framework, as well as the distributions of parameters corresponding to these factors. Key assumptions may also be made about the simulation setup and experimental conditions. Are the assumptions made for the computational model reasonable in the sense that they are consistent with the phenomena of interest? Can these assumptions be applied to various types of focal phenomena? Good assumptions should be reasonably realistic and generalizable.

Criterion #3: Rigor of computational modeling. Another important criterion is the rigor of computational modeling. Naylor et al. (1967) gave concrete guidelines for validating simulation models and, in the same line, Bratley (1983), Taber and Timpone (1995), and Railsback and Grimm (2011) have provided detailed recommendations. Editors and reviewers can choose to follow one or some of these guidelines. While various perspectives are presented in these guidelines, they point to some common questions in relation to the rigor of computational modeling. Is the computational model mathematically solid? Does it follow a standard modeling approach? If not, how is the model developed? Is it based on well-established models that have been validated before? If not, how is the model validated? When the novelty of modeling is high, validations by replicating prior results and/or comparing with empirical findings are needed (Dong, 2019).

Table 1. Assessment Criteria for Simulation Research

No.	Criterion	Questions
#1	Appropriateness of using simulation	• Is simulation an appropriate methodology to answer the research questions? • How suitable is the chosen modeling approach? • Does simulation offer unique theoretical insights into the phenomena of interest or can it be replaced by alternative methodologies?
#2	Reasonableness and generalizability of assumptions	• Are the assumptions made for the computational model reasonable in the sense that they are consistent with the phenomena of interest? • Can these assumptions be applied to various types of focal phenomena?
#3	Rigor of computational modeling	• Is the computational model mathematically solid? • Does it follow a standard modeling approach? If not, how is the model developed? • Is it based on well-established models that have been validated before? If not, how is the model validated?
#4	Effectiveness of research design	• Is the experimental design in simulation research appropriate to answer the research questions? • Are there major flaws in the research design that can potentially generate misleading results? • If simulation has critical limitations in terms of offering full answers to the research questions, are complementary methodologies used to address these limitations?
#5	Validity and robustness of results	• Do the simulation results capture the deep structure and patterns of the model or essentially reflect stochastic processes driven by randomness? • Do the simulation results still hold after considering confounding effects and addressing alternative explanations? • Are the simulation results stable across different experimental settings and insensitive to the specific chosen values of key parameters in experiments? • Are the simulation results consistent with prior findings and replicable in future research?
#6	Theoretical insights from findings	• Can the simulation findings significantly inform theory development? • Are the theoretical insights from the simulation findings important to extend or challenge extant theory? • How could the theoretical implications from the simulation findings guide future research and practice?

Criterion #4: Effectiveness of research design. A good simulation study should also answer the research questions with an effective research design. The research design for simulation often takes a form of experimental design, meaning that typical standards for assessing empirical study with experiments are applied (Dong, 2019). Is the experimental design in simulation research appropriate to answer the research questions? Are there major flaws in the research design that can potentially generate misleading results? If simulation has critical limitations in terms of offering full answers to the research questions, are complementary methodologies used to address these limitations? All these questions are relevant to evaluating the effectiveness of research design in simulation research.

Criterion #5: Validity and robustness of results. Regarding the validity and robustness of simulation results, there are questions related to internal validity (i.e., the trustworthiness of the findings) and external validity (i.e., the generalizability of the findings). In terms of internal validity, do the simulation results capture the deep structure and patterns of the model or essentially reflect stochastic processes driven by randomness? Do the simulation results still hold after considering confounding effects and addressing alternative explanations? Regarding external validity, are the simulation results stable across different experimental settings and insensitive to the specific chosen values of key parameters in experiments? Are the simulation results consistent with prior findings and replicable in future research? To ensure that simulation results are valid and robust, researchers need to repeat each run of simulation thousands of times, conduct robustness checks, and if possible, compare the results with empirical findings.

Criterion #6: Theoretical insights from findings. It is critical to interpret simulation results in a meaningful way and derive deep theoretical insights from the findings (Lave & March, 1975). Because simulation experiments are fully under researchers' control, it is possible to directly investigate the theoretical mechanisms underlying complex processes (Davis et al., 2007). Sometimes, counterintuitive and thought-provoking findings may be generated in simulation research to advance theory. Can the simulation findings significantly inform theory development? Are the theoretical insights from the simulation findings important to extend or challenge extant theory? How could the theoretical implications from the simulation findings guide future research and practice? Typical standards for judging the theoretical contributions of a study can be applied.

5 Concluding Remarks

This editorial provides an overview of three main simulation methods for IS research and offers timely guidelines for choosing simulation for IS research and evaluating the quality of simulation research. Agent-based modeling, fitness landscape modeling, and system dynamics modeling are powerful simulation methods to investigate various "systems" at the center of IS research. Research questions are always the most important for guiding methodological choices, while simulation is particularly suitable for answering questions with complexity of causal loops across levels and over time. Simulation could be a good methodological choice when there is a lack of quality data and the notable limitations of alternative methodologies can be addressed. To evaluate the quality of simulation research, I propose a list of six key criteria to guide assessment. Hopefully, this editorial can help IS researchers, editors, and reviewers choose, conduct, and assess simulation research, thus enriching the methodologies and knowledge creation in the IS field.

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