

On the Conceptualization of Information Systems as Socio-Technical Phenomena in Simulation-Based Research

Completed Research Paper

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Abstract

Information Systems (IS) are specified as complex socio-technical systems that display dynamic and emergent behaviors. Simulation-based studies provide a useful tool for analyzing such systems; however, the current presence and impact of simulation-based IS studies is limited. The socio-technical interactions and inherent dynamics of information systems make the development of IS simulations attractive, but challenging. Building simulations in this context requires both accurate conceptualizations of the underlying socio-technical systems as well as a sound transfer of these conceptualizations into simulation models. This study proposes an analysis framework that conjointly captures both the socio-technical system models as well as the derived simulation models. This allows for a critical assessment of the status quo of the extant simulation-based IS research. The identified relations are analyzed and seven propositions are derived, which provide guidance for prospective simulation-based research.

Keywords: Socio-technical approach, conceptual model, simulation model, simulation-based research

Introduction

Information systems (IS) are recognized as complex socio-technical systems in which humans, being part of social subsystems, and information technology (IT) artifacts, being part of technical subsystems, interact to process information (Lyytinen and Newman 2008; Mumford 2000). The overall behavior of such systems depends on a diverse set of often non-linear and dynamic mechanisms that relate to both the social and technical subsystems. The inherent complexity makes it difficult, if not impossible, to analytically describe IS behavior beyond isolated aspects of these systems (Hanseth and Lyytinen 2010; Harrison et al. 2007; Kulik and Baker 2008). This challenge, for instance, manifests in various studies that capture the difficulties of successfully conducting IS development projects, which often lead to high costs without significant gains (Heeks 2006; Savolainen et al. 2012; Yeo 2002).

These high costs prohibit a trial-and-error approach to IS development. They also limit researchers' opportunities to study artifacts, such as IS models, IS management methods, instantiations, and their

effects on their “three realities”: real tasks, real systems, and real users (Sun and Kantor 2006). Therefore, it has repeatedly been suggested to employ simulation methods for analyzing, understanding, and/or predicting IS behavior (Burton and Obel 2011; Davis et al. 2007; Harrison et al. 2007; Spagnoletti et al. 2013; Zhang and Gable 2014). For many simulation types, such as agent-based simulations or system dynamics, only the objects themselves and their relations to immediately affected entities need to be described (Bonabeau 2002). Depending on these descriptions on a local level, overall system behavior can then be observed by running the simulation. This allows the analysis of emergent behavior without requiring a precise understanding of the overall relations that lead to this behavior (Bonabeau 2002).

However, while simulation-based research provides substantial contributions in other disciplines, for instance in the natural sciences, the current presence and impact of simulation-based IS research is comparatively low (Zhang and Gable 2014). In a recent review of simulation studies, Zhang and Gable (2014) attribute a part of the low impact in IS to a difficulty in explaining the contribution of simulation studies, which often describe the technical details of the simulation in great detail to an audience that may lack the required technical background. They also hint at the methodological complexity of simulation-based IS research: building simulations to gain insight into IS behavior requires both an appropriate conceptualization of the constituent socio-technical system components as well as a sound transfer of these conceptualizations into simulation models and an application of appropriate simulation techniques (Chaturvedi et al. 2011).

Particularly, deriving appropriate conceptualizations of socio-technical systems is a necessary, but challenging, requirement for simulation-based IS research and is unique to social sciences in general and to IS research in particular. Studying IS as complex socio-technical systems requires a sophisticated approach that takes into account both the technical and social subsystems as well as their interdependencies. While simulation studies attempt to analyze system behavior, the resulting insights often seem to be oversimplifications of the phenomenon of interest and insufficient for reflecting the socio-technical nature of IS (Johnson 2000; Tsvetovat and Carley 2004). The simulation is only useful if its behavior sufficiently represents that of the respective real-world system. As the behavior of IS potentially depends on many very different aspects, including goals, values, and behavior of the people involved, it might not be clear a priori which of these aspects are relevant or how to identify them as such.

While the process of deriving conceptual models of socio-technical systems is well described in the IS literature (Hadar and Pnina 2006; Siau and Rossi 2011; Wand 2002) and while there exist some IS studies that use simulation models, there is not much information on how to construct simulation models from their underlying conceptual models or on how to develop conceptual models in a way that easily translates to simulation models in this context. Given the potential of simulations, and owing to the complex socio-technical nature of IS, the main objective of the paper at hand is to critically assess the status quo of extant IS literature on the conceptualization of socio-technical systems for simulation purposes. To this end, we suggest an analysis framework that conjointly captures both the socio-technical system models as well as the derived simulation models. This framework is presented along with the research method for the literature review and an explanation of the coding process in the next section. We then apply our analysis framework to prior simulation-based research in IS. In the concluding section, by means of analyzing and discussing the resultant insights and the identified patterns, we derive seven propositions that provide guidance for prospective simulation-based IS research.

Research Method and Analysis Framework

To critically assess the status quo of extant IS literature on the conceptualization of socio-technical systems for simulation purposes, we opt for a systematic literature review. In the following, we first develop the analysis framework that we used for reviewing the literature. We then report on our paper selection and the applied coding procedure.

Analysis Framework

According to the suggestions of Webster and Watson (2002), we use an analysis framework for guiding our literature review. We start by clarifying the scope of our investigation. Following Sargent (2005), the simulation model development process comprises distinct steps, starting with the selection of the real-world system of interest (problem entity) and ending with the actual implementation of the simulation

model (Figure 1). After selecting the problem entity, a *conceptual model* of the real-world system is derived by employing theoretical lenses (*system theories*). This model is then specified precisely enough to be useful as a basis for simulation. In a final step, the actual implementation of the simulation results in an executable *simulation model*.

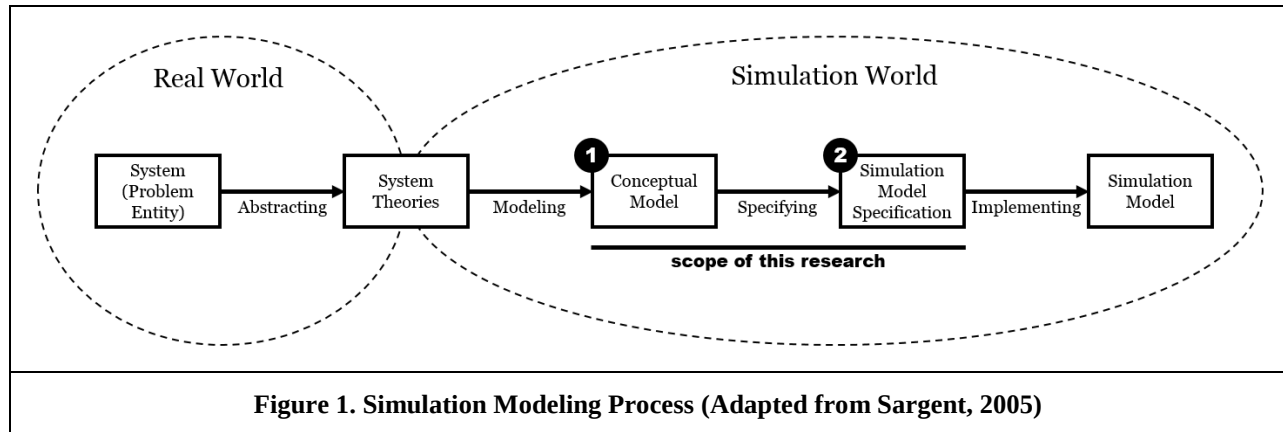


Figure 1. Simulation Modeling Process (Adapted from Sargent, 2005)

In this research, our scope is on the *conceptual model* as well as on the *simulation model specification*, since these steps, in particular, contribute to the difficulty of representing IS as socio-technical phenomena in simulation-based research. Consequently, the analysis framework introduces the constitutive elements of (1) the underlying *conceptual model* and (2) the resulting *simulation model*. These elements are derived based on a thorough examination of the pertinent literature. Table 1 gives an overview of the identified elements, which are explained in more detail in the remainder of this section.

Table 1. Overview of Analysis Framework Dimensions			
Analysis Element		Description	References
Theories		Which IS theories and which theories from reference disciplines have been used in the construction of the conceptual model?	(Davis et al. 2007; Kulik and Baker 2008)
Model Components	Actors	Are the main stakeholders and workers of the system modeled? (<i>yes/no</i>)	(Chaturvedi et al. 2011; Lyytinen and Newman 2008; Wu et al. 2015)
	Structure	Are, for instance, communication systems and workflows modeled? (<i>yes/no</i>)	
	Technology	Are the tools modeled e.g., software, hardware, and methodologies? (<i>yes/no</i>)	
	Tasks	Are goals and purposes, or deliverables, modeled? (<i>yes/no</i>)	
	Environment	Are external influences on the system modeled? (<i>yes/no</i>)	
Model Properties	Socio-technical modeling	Are interactions between social systems (e.g., human agents) and technical systems modeled? (<i>yes/no</i>)	(Gregoriades and Sutcliffe 2008; Lamb and Kling 2003)
	Closed boxing	Is the model more confirmatory or exploratory in nature? (<i>closed/partly open/open</i>)	(Lyytinen and Newman 2008)
	Complexity	How complex is the conceptual model? (<i>complex/moderate/simple</i>)	

Model Properties (continued)	Punctuated change	Are linear adaptive changes and punctuated changes modeled? (<i>yes/no</i>)	(Lyytinen and Newman 2008; Wu et al. 2015)
	Internal dynamics	Is the internal system dynamic or static? (<i>static/dynamic</i>)	(Allen and Varga 2006; Chaturvedi et al. 2011; Porra 1999; Porra 2010; Wu et al. 2015)
	Behavior dependent on history	Is system behavior dependent on previous states as compared with only the current state? (<i>yes/no</i>)	
	Dynamic structures	Is the system structure static or does it change over time? (<i>static/dynamic</i>)	
	Dynamic system size	Does the size of the system change over time? (<i>static/dynamic</i>)	
	Dynamic lifetime of objects	Do objects have a dynamic lifetime? Are agents added to or removed from the system? (<i>yes/no</i>)	
	Teleology	Are goals and purposes included in the model? (<i>yes/no</i>)	(Barbati et al. 2012; Raghu 2004)
	Control	Is control (e.g., via control-feedback loops or control hierarchies) modeled? (<i>yes/no</i>)	
IS Change Model	IS development model	Are IS development processes described as a part of the conceptual model? (<i>yes/no</i>)	(Alter 2008; Parunak et al. 1998; Reimers et al. 2014)
	Interventions	Are external interventions that guide the IS development process modeled? (<i>yes/no</i>)	
	Work system	Is the information processing system itself included in the model? (<i>yes/no</i>)	
	Building system	Are the building systems that steer work system change modeled? (<i>yes/no</i>)	
	Environmental context	Are external influences on the IS development process modeled? (<i>yes/no</i>)	
Simulation Model	Simulation approach	Which technical approach was used to implement the simulation? (<i>stochastic processes/analytical/system dynamics/agent-based/human-based</i>)	(Harrison et al. 2007; Spagnoletti et al. 2013)
	Simulation use	What is the purpose of the simulation in the context of the research? (<i>prediction/proof/discovery/explanation/critique/prescription/empirical guidance</i>)	(Davis et al. 2007; Harrison et al. 2007)
	Validation/grounding	How is the relation between the simulation model and the real-world system validated? (<i>animation/face validity/comparison to other models/degenerate tests/extreme condition tests/predictive validity/internal validity/parameter variability – sensitivity analysis/historical data validation/operational graphics/traces/rationalism/event validity/Turing tests</i>)	(Davis et al. 2007; Sargent 2005)
	Probabilistic model	Is the simulation probabilistic or deterministic? (<i>probabilistic/deterministic</i>)	(Dooley 2002)

Since “any reasonably comprehensive simulation of organizations must be constructed from insights made with regard to how organizations have been observed to operate,” an analysis of fundamental

theories is of great help (Kulik and Baker 2008, p. 88). The importance of theory-informed conceptualization is underlined by Sargent's choice of including the abstraction of a system theory as the basis of the conceptual model as a fundamental step in the simulation model development process (Figure 1)(Sargent 2005). Thus, our analytical framework includes the theoretical basis used as a foundation for the conceptual model. Literature shows that IS research increasingly relies on concepts and ideas from other areas, such as management and organization sciences; therefore, not only generally recognized IS theories are included in our analysis, but also other commonly used theories from reference disciplines (Grover et al. 2006).

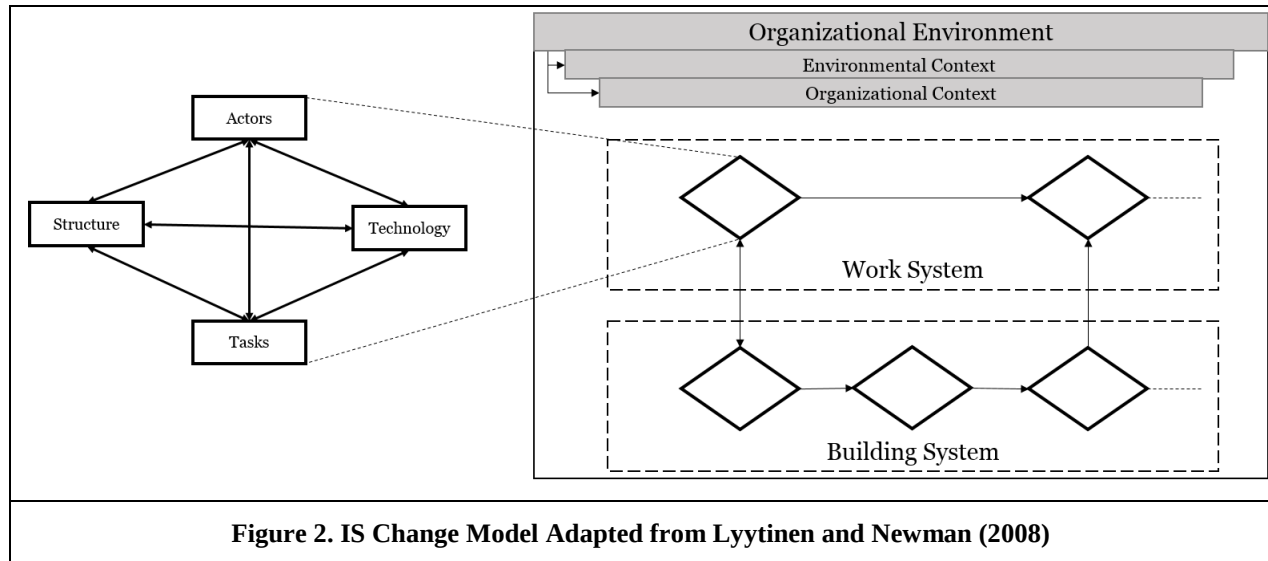
For analyzing (1) the *conceptual model*, we take a socio-technical systems perspective (Barbati et al. 2012; Chaturvedi et al. 2011; Gregoriades and Sutcliffe 2008; Lamb and Kling 2003; Lyytinen and Newman 2008; Porra 1999; Wu et al. 2015). This results in three different classifications: (1.1) *model components* that describe which components of a socio-technical IS are included in the model, (1.2) *model properties* that describe important properties of the conceptual model itself, and (1.3) the *IS change model*, which describes the IS development process. Note that the modeling of these aspects is strongly influenced by the underlying *theories* that are used as a basis for the conceptual model (Davis et al. 2007).

From a socio-technical systems perspective, information systems can be seen as consisting of five basic components (see 1.1): *tasks, actors, structure, technology, and environment* (Gregoriades and Sutcliffe 2008; Lyytinen and Newman 2008; Wu et al. 2015). We base our view of IS on the punctuated socio-technical IS change (PSIC) model of Lyytinen and Newman (2008) in which *tasks, actors, structure, and technology* interact with each other and are embedded in the organizational *environment* that is driving and influencing change (see the left side of Figure 1).

Derivation of the *model properties* and the *IS change model's* constitutive elements (see 1.2 and 1.3) is based on a consolidation of relevant discussions in the literature. Reimers et al. (2014) provide a recent survey of IS change theories and, although they are doubtful that any such currently available theory accurately captures IS change, they do provide interesting viewpoints for looking at the dynamics of socio-technical systems. According to Reimers et al. (2014), IS development occurs through a number of local adaptive changes in combination with the emergence of new practices on a higher level. They identify two approaches to IS change that adequately capture this process, evolutionary and dialectical change, and, respectively, two well-developed theoretical models, the PSIC model of Lyytinen and Newman (2008) and the "colonial systems" (CS) model of Porra (1999; 2010).

With regard to dynamics and the IS change model, the PSIC model assumes that IS development is not only driven by a continuous linear series of small incremental changes as suggested by Newman and Robey's social process model (Newman and Robey 1992), but additionally shows emergent, disruptive changes, termed punctuated changes, which are triggered by the underlying "deep structure" of the system (Lyytinen and Newman 2008). Since IS are recognized as work systems, i.e., "system[s] in which human participants and/or machines perform work (processes and activities) using information" (Alter 2008), and show low malleability (Alter 2002), their development is carried out using analytically separate building systems.

In this setting, punctuated changes have been recognized to originate from one of several areas (Figure 2). First, sequential changes within the work system or the building system themselves can, over time, lead to misalignments between the constituent socio-technical components (actors, structure, technology, and tasks), which, in turn, are resolved through disruptive changes and major adaptations of the overall system (Lyytinen and Newman 2008). These misalignments can either directly lead to a change in the work system or be translated into a separate building system in which they are then resolved, or the adaptations are translated back to the work system itself. Second, IS are not isolated systems but are affected by changes in their surrounding environment. This type of change, driven from the organizational environment, is conceptually split into two parts: the environmental context, i.e., "critical events concerning [the] organization's social, economic, political, regulatory and competitive context" (Lyytinen and Newman 2008, Fig. 4., p. 600) and the organizational context, i.e., "events concerning the resource, authority, culture, [and] politics of IS change" (Lyytinen and Newman 2008, Fig. 4., p. 600).



The colonial systems model has a different focus. According to Ashby (1972), there exist only two essential system types: mechanistic systems and organic systems. As the behavior of IS depends to a large extent on the complex interactions between human actors, the mechanistic viewpoint seems not to fit our perspective. Inspired by biological systems, the colonial systems model specifies socio-technical systems “as a collection of individuals who share a history and an environment and who cooperate directly or indirectly for the maintenance of the [system]” (Porra 1999). This approach matches the complex systems perspective on the modeling and development of IS, which lays its focus on the dynamic and complex relations of such socio-technical systems (Allen and Varga 2006).

We integrate these ideas and combine the classification schema of Lyytinen and Newman (2008), Mayr (1982), and Porra (1999). This leads to the following properties of socio-technical system models (see 1.2) in IS: *socio-technical modeling*, *closed boxing*, *complexity*, *punctuated change*, *internal dynamics*, *behavior dependent on history*, *dynamic structures*, *dynamic system size*, *dynamic lifetime of objects*, *teleology*, and *control*. For the IS change model (see 1.3), the following analysis elements were identified: *IS development model*, *interventions*, *work system*, *building system*, and *environmental context*.

For analyzing (2) the *simulation model*, we include the *simulation approach* from Davis et al. (2007) that was already employed in the classification of Spagnoletti et al. (2013) and categorizes simulations by implementation approaches, namely, *stochastic processes*, *analytical*, *system dynamics*, *agent-based*, and *human-based*. On the technical side, we also distinguish *probabilistic* and *deterministic* simulations, as suggested by Dooley (2002). We additionally classify simulations by their intended purpose, as this significantly affects the development process of the simulation model (Davis et al. 2007). Harrison et al. (2007) suggest the following *uses* for simulation: *prediction* (how are model variables related), *proof* (show that certain system behavior exists), *discovery* (discover unexpected consequences of interactions), *explanation* (explain why the system behaves in a certain way), *critique* (test existing theories), *prescription* (suggest how to best interact with or within the system), and *empirical guidance* (derive hypotheses for empirical testing). Multiple uses may apply to a single simulation.

Another central aspect for this research is how researchers validated their models, since this explains and justifies the connection between the simulation model and the underlying real-world system. In our analysis, we follow the comprehensive classification of simulation model validation techniques from Sargent (2005): *animation* (display operational behavior graphically, e.g., show the movements of actors), *face validity* (get expert opinions on the model and its behavior), *comparison with other models* (compare the model with other validated models), *degenerate tests* (test the degeneracy of the model's behavior by appropriate parameter selections), *extreme condition tests* (check if the model behaves reasonably when extreme values are selected for model parameters), *predictive validity* (use the model to make predictions and compare them with real-world behavior), *internal validity* (run probabilistic models multiple times and check for consistency), *parameter variability – sensitivity analysis* (modify input parameters and analyze the effects), *historical data validation* (use historical data not only for

building but also for testing, e.g., by splitting the dataset in half), *operational graphics* (display the values of performance measures for the system over time), *traces* (trace the behavior of specific objects in the model), *rationalism* (deduce the model logically), *event validity* (compare simulated events with those occurring in real-world systems), and *Turing tests* (check if experts can discriminate between model and real-world system output). A given simulation may use multiple techniques to establish the validity of the simulation model.

Paper Selection

To select the relevant literature for our review, we adopt the database of the collected papers in Spagnoletti et al.'s (2013) recent literature review instead of repeating the paper selection procedure, owing to two main reasons. First, both studies share a common literature scope, which is the use of simulation in IS research. Therefore, the selected papers in Spagnoletti et al. (2013) reflect the relevant literature for our study. Second, Spagnoletti et al. (2013) take advantage of a rigorous process for their selection of relevant literature, so that we can ensure the reliability of the literature search procedure and build on a scientifically sound database. Spagnoletti et al. (2013) use five simulation approaches from Davis et al. (2007) (system dynamics, NK fitness landscape, genetic algorithms, cellular automata, and stochastic processes), along with the more general word "simulation," as keywords to search for relevant literature in several scientific databases. This search results in the retrieval of 88 papers, 19 of which are excluded since they focus on simulation as a topic instead of employing it as a research method. The final result is a database of relevant papers containing 69 papers from the AIS's basket of top journals (*ISR*, *MISQ*, *JAIS*, *JMIS*, *JSIS*, *EJIS*, and *JIT*). However, Spagnoletti et al.'s (2013) database of papers includes publications up to 2012. Therefore, we extended this set of papers by applying exactly the same inclusion and exclusion procedures as employed by Spagnoletti et al. (2013) for the time period of 2012–2014. This resulted in identifying 18 additional papers, of which 4 papers were excluded. The remaining 14 papers were added to the set of Spagnoletti et al. (2013), leading to a final set of 83 papers.

Coding Procedure

The introduced analysis framework was used to develop a comprehensive coding scheme. The collected papers were coded by two of the authors of the paper at hand while the coding scheme was discussed among all authors. To ensure the uniformity of the coding and to avoid ambiguity, the coding scheme was discussed intensively in a series of five workshops, totaling 11.5 hours, with authors to reach a common understanding on each element of the given coding scheme. In the workshops, the authors discussed the underpinning criteria for each of the coding scheme's elements, relying on the provided arguments in the referenced studies upon which the analysis framework and, consequently, the coding scheme, is built. The latter resulted in the first version of a detailed guideline for coding. We reached inter-coder concordance, i.e., consensus among independent coders who are using the same coding scheme, on the coding of the content of interest, in two steps. In the first step, a pilot coding, two of the authors coded the same set of papers independently based on the initial coding guideline. Since the coding guideline mainly required judgment on the presence or absence of specific criteria in each paper, this was straightforward to do and reduced the potential for coders' subjective biases. In the second step, the authors discussed the few disagreements among coders in the pilot coding endeavor to ensure adequate inter-coder concordance. This brought about the development of the final coding guideline that we used to code all the papers, including a re-coding of the pilot papers.

Results

As our analysis framework is rather comprehensive, not every relation among the different dimensions can be presented here¹. Nevertheless, to make our analysis of prior research as exhaustive as possible, we have selected those elements of the analysis framework that (i) provide the most interesting insights from our dataset, especially from a socio-technical perspective, and (ii) facilitate cross-element analysis of prior research. The selected analysis elements are grouped into the following categories:

¹ We refer readers who are interested in building IS simulations to the entire dataset at <https://dx.doi.org/10.13140/RG.2.1.3381.6808>

- i. *Model components*: A central part during the process of model construction is the selection of the relevant system components (i.e., *actors*, *tasks*, *structure*, *technology*, and *environment*) that need to be included in the model. Therefore, we analyze the relation between the components of an IS, and the simulation approach and use.
- ii. *Model properties*: The relations among the use of the simulation and the properties of the underlying conceptual model, which were developed in the analysis framework, are presented in this section.
- iii. *Validation*: A useful simulation model needs to appropriately represent the underlying real-world system. Thus, we analyze how the validity of this representation is tested in simulation-based IS research.
- iv. *Theories*: IS research relies on theory that describes, explains or predicts the specific behaviors of socio-technical systems by focusing on respective constructs and relations (Kulik and Baker 2008). These system theories provide justificatory knowledge for simulation model development (Gregor 2006). We thus analyze the usage of theories in simulation-based IS research.

Model Components

To analyze which components of a socio-technical system are covered by the model development process, we first calculate the percentage of publications that include a socio-technical system component in the conceptual model and group them by the respective simulation approach according to Spagnoletti et al. (2013) (Figure 3).

	Actors	Structure	Technology	Tasks	Environment	Average
Stochastic Processes	☉ 24%	○ 6%	○ 18%	○ 18%	○ 12%	○ 15%
Analytical	◐ 48%	◐ 52%	◐ 44%	◐ 67%	◐ 48%	◐ 52%
Human-Based	● 100%	◐ 33%	◐ 50%	● 100%	◐ 67%	◐ 70%
System Dynamics	◐ 71%	● 100%	◐ 43%	◐ 57%	● 86%	◐ 71%
Agent-Based	● 95%	● 80%	◐ 55%	● 80%	◐ 65%	◐ 75%
Average	◐ 64%	◐ 51%	◐ 42%	◐ 64%	◐ 51%	

Figure 3. Components Modeled by Simulation Approach²

Actors and *tasks* are the components most often included in the conceptual model. In addition, an increasing coverage of socio-technical system components can be observed when going from more direct simulation approaches, i.e., approaches such as *statistical techniques* and *analytical models*, where relations are explicitly described, toward more indirect simulation approaches such as *agent-based* simulation models, which often rely on a local description of interaction patterns (Carley 2001; Dooley 2002; Parunak et al. 1998). Owing to the nature of the simulation approach, *human-based* simulations necessarily include *actors* and *tasks* in the conceptual model, and *system dynamics* models rely on a precisely defined *structure*.

Figure 4 shows the same socio-technical system components grouped by use of the simulation. A tendency toward a more complete conceptualization can be observed for more open simulation uses such as *discovery*, i.e., simulation uses with an a priori open result, whereas simulations that are used to test a specific proposition, such as *critique* and *proof*, employ more selective conceptualizations.

² Note that the averages in Figure 3, as well as in the following analyses, show percentages of the total number of publications in a given category. For example, with regard to the simulation approach, there are 83 papers in total, 17 papers in the group *stochastic processes*, 27 in *analytical processes*, 12 in *human-based*, 7 in *system dynamics* and 20 in *agent-based*. Therefore the average coverage for the component actors is calculated as $(17 \cdot 24\% + 27 \cdot 48\% + 12 \cdot 100\% + 7 \cdot 71\% + 20 \cdot 95\%) / 83 = 64\%$.

	Actors	Structure	Technology	Tasks	Environment	Average
Critique	☐ 27%	☐ 18%	☐ 18%	☐ 9%	☐ 9%	☐ 16%
Proof	◐ 56%	◐ 44%	◐ 44%	◐ 48%	◐ 41%	◐ 47%
Empirical						
Guidance	◐ 55%	◐ 55%	◐ 55%	◐ 55%	◐ 45%	◐ 53%
Prescription	◐ 61%	◐ 50%	◐ 42%	◐ 69%	◐ 56%	◐ 56%
Prediction	◐ 76%	◐ 56%	◐ 40%	◐ 72%	◐ 76%	◐ 64%
Explanation	◐ 77%	◐ 57%	◐ 51%	◐ 79%	◐ 68%	◐ 66%
Discovery	● 100%	◐ 63%	◐ 63%	● 84%	◐ 74%	◐ 77%

Figure 4. Components Modeled by Simulation Use

Note that in both Figures 3 and 4, the low coverage for the simulation approach *stochastic processes* and the use *critique* is partly due to a discussion of quantitative techniques in IS research, which relies on data generated by Monte Carlo simulations that do not represent any socio-technical system³.

Model Properties

Table 2 shows the number of papers in each simulation approach based on their model properties in terms of complexity and closed boxing (Lyytinen and Newman 2008).

Table 2. Complexity and Closed Boxing by Simulation Approach					
Simulation Approach	System Complexity		Closed Boxing		
	Complex	Moderate	Closed	Partly Open	Open
Agent-Based	20	0	7	11	2
Human-Based	11	1	8	4	0
System Dynamics	7	0	5	2	0
Analytical	23	4	27	0	0
Stochastic Processes	9	8	17	0	0
Total	70	13	64	17	2

Almost all analyzed papers are for rather *complex* and *closed* systems. System complexity was coded as being *simple*, *moderate*, or *complex*, but none of the conceptual models from the set of analyzed papers was considered to be *simple* and most were considered *complex*. Similar results hold for the *openness* of the conceptual models. A gradual increase in *complexity* and *openness* can be observed when going from more direct simulation approaches (*stochastic processes/analytical*) toward more indirect approaches (*agent-based/human -based*).

³ There is an ongoing discussion on properties of quantitative research methods, initiated by (Chin et al. 2003), which uses Monte Carlo simulation to generate sample data. In this type of research, the simulation model does not relate to a real-world system in any way, but only generates “noisy” data from an artificial structure, which are then used for tests. These studies do not model any socio-technical real-world components or dynamics and, therefore, lead to low percentages in the respective dimensions of the analysis framework for the simulation approach *statistical techniques* and the simulation use *critique*.

Figure 5 shows the percentage of papers that included specific properties in the conceptual model. A first observation is that IS development and change drivers are rarely modeled (*IS development, building system, interventions*). Only changes resulting from the environmental context are included in approximately half of the cases. When sorting the simulation uses by the average percentage of papers, which included specific model properties, papers with a more open simulation use show a higher percentage of modeled properties, such as *dynamics*. Three notable exceptions can be identified in this pattern:

- 1.) When simulation is used for *empirical guidance* and *discovery*, the conceptual model uses dynamic structures more often. Furthermore, conceptual models that include punctuated changes and in which change is history-dependent, i.e., dependent on previous states of the system, are employed more frequently.
- 2.) Simulations that are used for *discovery* rarely build on conceptual models in which objects have a dynamic lifetime.
- 3.) In all cases, simulations used for *prediction* are built on conceptual models that include the environmental context as a driver for IS change.

	Critique	Proof	Empirical Guidance	Prescription	Prediction	Explanation	Discovery	Average
Interventions Modeled	○ 0%	○ 7%	○ 0%	○ 14%	○ 16%	● 23%	○ 16%	○ 14%
IS Development	○ 9%	○ 11%	○ 18%	○ 17%	○ 8%	○ 19%	○ 16%	○ 15%
Building System	○ 0%	○ 15%	○ 18%	● 22%	● 20%	● 23%	○ 16%	○ 19%
Dynamic Structures	○ 9%	○ 19%	● 36%	○ 11%	○ 24%	○ 21%	● 37%	● 21%
Punctuated Change	○ 0%	○ 19%	○ 45%	● 25%	● 44%	● 32%	● 68%	● 33%
Behavior Dependent on History	○ 0%	○ 19%	○ 55%	○ 14%	● 36%	○ 45%	● 68%	● 34%
Dynamic Lifetime of Objects	○ 0%	● 30%	○ 27%	● 28%	○ 40%	● 62%	○ 16%	● 36%
Dynamic System Size	○ 9%	○ 41%	○ 27%	● 33%	○ 40%	○ 47%	○ 47%	○ 39%
Environmental Context	○ 0%	● 26%	● 36%	● 22%	● 100%	○ 55%	○ 58%	○ 46%
Control Modeled	○ 9%	○ 44%	○ 36%	○ 44%	● 64%	● 68%	● 74%	○ 54%
Socio-Technical Modeling	○ 27%	○ 52%	○ 55%	○ 44%	○ 52%	○ 64%	● 95%	○ 57%
Dynamic System	○ 27%	○ 56%	○ 45%	● 61%	● 80%	● 74%	● 84%	● 66%
Goals Modeled	○ 18%	○ 48%	● 64%	● 67%	● 72%	● 83%	● 84%	● 68%
Work System	○ 36%	○ 70%	● 64%	● 75%	● 88%	● 83%	● 95%	● 77%
Probabilistic	● 91%	● 85%	● 100%	● 86%	● 80%	● 85%	● 100%	● 88%
Average	○ 16%	○ 36%	○ 42%	○ 38%	○ 51%	○ 52%	○ 58%	

Figure 5. Model Properties by Simulation Use

Validation

This section presents results with regard to the employed model validation and verification techniques according to Sargent (2005). Table 3 shows that the more varied uses a simulation model has, the more validation techniques are employed to establish and justify the connection to the underlying real-world system.

For each simulation use, Figure 6 shows the percentage of papers employing a specific validation technique, not including percentages for the validation techniques *animation*, *Turing tests*, and *degenerate tests*, which were not employed in any of the 83 analyzed papers. While some validation techniques, such as the *comparison* of the simulation model with other well-established models or performing tests for *internal validity* in probabilistic simulations, are employed frequently, a large set of the techniques suggested by Sargent (2005) is mostly disregarded. The average number of techniques employed to establish simulation model validity is higher for more open simulation uses, such as *discovery*, when compared with more closed uses, such as *critique* and *proof*.

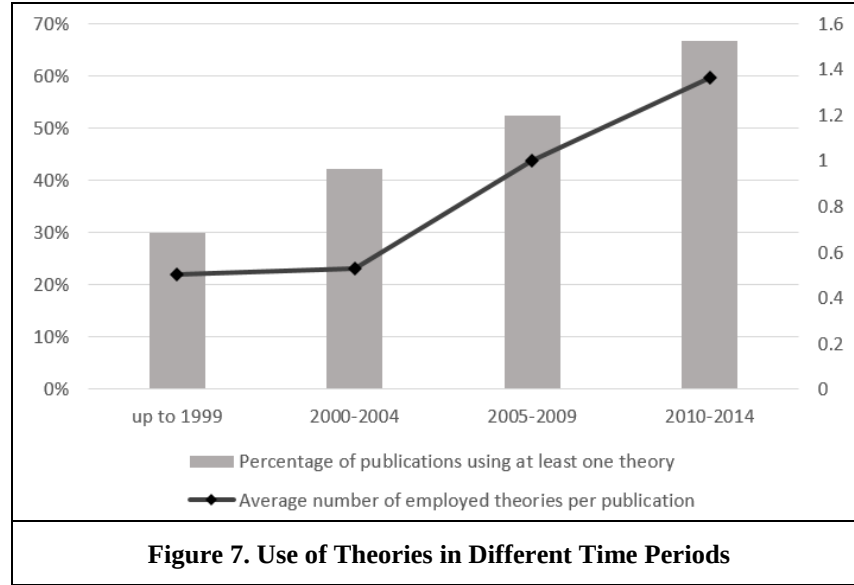
Table 3. Number of Employed Validation Techniques				
		Number of Uses		
		1	2	3
Number of employed validation techniques	1	7	19	1
	2	3	12	5
	3	4	10	10
	4	0	5	4
	5	0	0	2
	6	0	0	1

	Average Number of Validation Techniques	Face Validity	Comparison to other Models	Extreme Condition Tests	Predictive Validation	Internal Validity	Parameter Variability - Sensitivity Analysis	Historical Data Validation	Operational Graphics	Traces	Rationalism	Event Validity
Critique	1,78	○ 0%	● 44%	○ 0%	○ 11%	● 78%	● 22%	○ 0%	○ 11%	○ 0%	○ 11%	○ 0%
Proof	2,00	○ 0%	● 47%	○ 5%	○ 16%	● 42%	● 32%	● 26%	○ 11%	○ 0%	○ 5%	○ 5%
Emp. Guidance	2,14	○ 14%	● 57%	○ 14%	○ 0%	● 86%	○ 0%	○ 14%	○ 0%	○ 0%	○ 0%	● 29%
Explanation	2,45	● 23%	● 75%	○ 8%	○ 13%	● 20%	○ 25%	● 33%	○ 10%	○ 0%	○ 5%	● 20%
Prescription	2,50	○ 13%	● 66%	○ 9%	○ 19%	○ 19%	● 38%	● 31%	○ 13%	○ 3%	○ 0%	○ 19%
Prediction	2,80	● 20%	● 70%	○ 10%	○ 15%	● 35%	● 35%	● 35%	● 20%	○ 5%	○ 0%	● 35%
Discovery	2,87	● 33%	● 87%	● 20%	● 20%	● 40%	○ 13%	● 40%	○ 7%	○ 7%	○ 0%	● 20%

Figure 6. Employed Validation Techniques by Simulation Use

Theories

The use of grand theories is ever increasing in IS research. A wide range of theories from reference disciplines, such as the organization, management, and computer sciences, are used as an analytical basis to guide both theory building and theory testing in IS research (Bakos and Kemerer 1992; Orlikowski and Barley 2001). Even though, to some extent, boundaries of theories are not clear-cut across disciplines, we reached a list of theories in our analysis that can be categorized as: commonly used theories (from reference disciplines) in IS, IS theories (either IS-specific theories or reference discipline-led IS theories), and discipline-specific theories (such as theories in computer science or economics). Our analysis of extant simulation-based research reveals that, similar to the trend in the IS discipline in general, the development of theory-based conceptual models in simulation-based studies is growing (Table 4 and Figure 7). More than 60% of the analyzed papers that were published between 2010 and 2014 employ at least one theory when constructing their conceptual model. Compared with the 1990s and 2000s, the use of theories when constructing conceptual models as a basis for simulations has substantially increased in the 2010s, so that the more recent studies more frequently used theoretical lenses.



The most frequently employed theories in simulation-based studies are both: (i) commonly used theories in IS or IS theories (e.g., *game theory*, the *technology acceptance model*, *competitive strategy*, or *portfolio theory*) as well as (ii) discipline-specific theories (e.g., *auction* and *queuing theories* in economics and computer science), which are easily applicable to the specific research questions of a given study. In effect, researchers exploited theories that can be easily translated into mathematical models and that help researchers to systematically derive different scenarios subject to simulation. Other commonly used theories in IS, such as *agency theory*, *institutional theory*, *transaction cost theory*, *diffusion of innovations*, *contingency theory*, or the *resource-based view of the firm*, are used once or twice in the set of investigated papers.

Simulation Approach	Average Number of Theories Used per Publication	Percentage of Publications Using at Least One Theory
Stochastic processes	0,41	41%
Human-based	0,71	42%
System dynamics	1,00	29%
Analytical	1,29	74%
Agent-based	2,00	80%
Total	1,19	60%

Regarding simulation approaches, theories are mostly exploited in *agent-based* and *analytical* simulations (Table 4). It turns out that the use of theories is common in studies that aim to investigate (i) the complex behavior of system actors, often using *agent-based* simulations, or (ii) the development of formal models, e.g., via *analytical simulations*, rather than on their statistical validation. For this group of simulations, existing theories represent building blocks for the conceptual models (Davis et al. 2007). Furthermore, simulation studies also employ complementary theories, i.e., a synergic combination of theories that aims at a comprehensive analysis of the phenomenon of interest (Tiwana and Bush 2007); for instance, the *resource-based view of the firm* along with *transaction cost theory*. The use of complementary theories is more common in *agent-based* and *analytical* simulations.

Discussion and Conclusion

An analysis framework was developed to understand how IS researchers conceptualize socio-technical information systems in simulation-based research. The application of this framework to the selected set of 83 simulation-based research papers from IS yields a number of interesting observations and allows us to identify relations among the different dimensions described by the analysis framework. Following the same structure that is used in the results section, we now discuss these insights and derive a set of seven propositions (Table 5) that provides guidance for the conceptualization of IS as socio-technical systems for simulation-based research. We illustrate these propositions with an example of how simulations can help overcome some of the limitations of more traditional research approaches with regard to complex and emergent socio-technical phenomena in a specific case.

Table 5. Propositions on the Conceptualization of IS as Socio-Technical Systems in Simulations	
Analysis Dimension	Propositions
Model components	P1. More open simulation uses require a more complete coverage of socio-technical system components in the conceptual model. P2. More indirect simulation approaches require a more complete coverage of socio-technical system components in the conceptual model.
Model properties	P3. Explorative simulation uses require a better understanding of structural dynamics and socio-technical change processes. P4. When using simulations to make predictions, it is essential for the conceptual model to include external influences on the system.
Validation	P5. Simulation model validation in IS research is an iterative process toward better simulation models and ideally involves a diverse set of techniques as well as empirical data. P6. More open simulation uses require a higher validation effort to establish and justify the connection between the simulation model and the represented real-world system.
Theories	P7. The investigation of IS phenomena as socio-technical systems through simulation-based research is facilitated by the use of theories that conceptualize the non-deterministic nature and inherent dynamics of these phenomena.

Simulations are often used for testing specific statements about real-world systems, which is the case for the uses *proof* and *critique* (Sargent 2005). At the other end of this spectrum are simulation uses that are more open with regard to the expected results, i.e., before running the simulation, it is not clear what precisely the expected insight from the simulation is, as is the case for the simulation type *discovery*. As Figure 4 suggests, more open simulation uses require a more complete coverage of socio-technical system components in the underlying conceptual model. This insight is in line with the existing discourses on the creation of conceptual models: (i) ontologically adequate conceptual models need to consider all potentially relevant aspects, including behaviors and co-evolutionary structures (McKelvey 2002); or else, (ii) if the simulation has a very clear goal and scope, a more formal model and limited coverage of components may be better suited (Adner et al. 2009).

A similar relation can be observed with regard to simulation approaches: some approaches describe system behavior directly at the outset, such as *analytical* or *statistical* simulations. Other approaches, such as *agent-based* simulations or simulations involving *human* participants, often describe interaction patterns on a local level (Bonabeau 2002). Figure 3 shows an increasing coverage of socio-technical system components when going from more direct analytical simulation approaches toward more indirect simulation approaches. Therefore, we propose the following:

P1. More open simulation uses require a more complete coverage of socio-technical system components in the conceptual model.

P2. More indirect simulation approaches require a more complete coverage of socio-technical system components in the conceptual model.

As an example, Johnson et al. (2014) aim at understanding the generative mechanisms of power distributions in online communities, i.e., non-normal distributions of power, where a few community members are very influential and highly connected, whereas most community members have little influence. There are several competing theories that might explain how these distributions are created. It is unclear whether a single theory explains the entire phenomenon or, if it is, indeed, as the authors propose, a combination of multiple mechanisms working concurrently. Therefore, an indirect simulation approach is chosen that does not model global system behavior, but, instead, focuses on the behaviors and perceptions of individual agents. This, in turn, requires all aspects relating to individual behavior and all relevant structures to be included in the model. Since the simulation is, “open” with regard to which theory, or which combination of theories, is applicable, the inclusion of all components that are referred to by the different theories is also required.

With regard to the properties of the conceptual model, the socio-technical models in the selected set of papers are all rather *complex* (Table 2). We believe this to be due to the nature of the method. If the conceptual models were simple, then simulation would not be needed for analyzing them (Harrison et al. 2007). With regard to closed boxing, most conceptual models were built with a very specific intent, which explains the classifications in Table 2. There are only a few exceptions, mostly agent-based approaches, which rely on more open conceptual models.

Figure 5 shows that IS development (15%) and related components (building system: 19%, interventions: 14%) are rarely included in the conceptual model. This may be due to the inherent complexity of such processes (Hanseth and Lyytinen 2010; Harrison et al. 2007; Kulik and Baker 2008). We now analyze the three exceptions that can be observed in the pattern of model properties and are marked by the circles in Figure 5.

First, the simulation uses *discovery* and *empirical guidance* to show a more detailed modeling of dynamic structures and change mechanisms. These two uses are both characterized by being explorative in nature, i.e., aimed at the discovery of unexpected consequences and at the generation of new empirical strategies (Harrison et al. 2007). In the underlying set of analyzed papers, this interest in unintended and unexpected behaviors is an important aspect for the design of the conceptual model and requires a precise understanding and modeling of dynamics and IS change mechanisms. This insight is in line with the existing discussions on computational models that go “beyond what is to explore possibilities and examine boundaries to what might be” (Burton and Obel 2011, p. 1197). These models often need to include dynamic processes, such as organizational and individual learning, decision-making, innovation, and imitation (Burton and Obel 2011).

P3. Explorative simulation uses require a better understanding of structural dynamics and socio-technical change processes.

Second, when simulations are used for making predictions, influences from the environmental context are always included in the conceptual model. As this type of simulation is used to predict how system behavior changes under varying external conditions and influences, the external environment is an essential component of the conceptual model (Fabien et al. 2009; Helleboogh et al. 2007). In these models, dynamics are often explicitly modeled as a part of the simulated environment and not just a consequence of interactions between the agents. This enables researchers to capture dynamisms that originate from other sources beyond the control of the agents, which allows for a better representation of the simulated real-world phenomenon (Fabien et al. 2009).

P4. When using simulations to make predictions, it is essential for the conceptual model to include external influences on the system.

Third, simulations that are used for discovering new phenomena rarely include objects with a dynamic lifetime. In the analyzed set of papers, this is mostly due to the single components (e.g., agents) already being rather complex. While these components may change their behaviors over time, they are rarely added or removed from the simulation model. In those cases, this is mostly a consequence of a dynamic object lifetime not providing any additional insight in this specific set of simulations, rather than a general observation that will hold true for future research.

As an illustration of P3 and P4, the research of Johnson et al. (2014) explains and makes predictions about the behavior of online communities. This requires the employed conceptual model to include the dynamic structures and interactions in such communities. Furthermore, one needs to explicitly describe how new people join and how current members leave a community, in order to accurately represent the behavior of real-world messaging communities, on which the simulation model is based.

With regard to model validation, Sargent (2005) suggests an eight-step procedure that guides the identification and application of appropriate validation techniques for the conceptual and simulation models. This leads to an iterative process in which the simulation is tested and refined in each iteration. As a minimum, it is suggested to use face validity tests during each iteration, which, according to our analysis, is rarely explicitly described in simulation-based IS research (Figure 6). Multiple validation techniques should be used to build confidence in the connection of the simulation model to the underlying real-world system, including the use of empirical data (Davis et al. 2007). Figure 6 shows that while some validation techniques, such as the comparison of the simulation model with other well-established models or performing tests for internal validity in probabilistic simulations, are employed frequently, a large set of the suggested techniques is mostly disregarded. However, especially in the context of complex and dynamic socio-technical IS phenomena, the extent to which the simulation model accurately captures the essential behavior of the real-world system is often unclear. Therefore, we want to reemphasize the need for a thorough and well-documented validation procedure as has been stressed, for instance, by Davis et al. (2007) and Harrison et al. (2007).

P5. Simulation model validation in IS research is an iterative process toward better simulation models and ideally involves a diverse set of techniques as well as empirical data.

Figure 6 shows an increase in the average number of employed validation techniques when going from more closed simulation uses such as *critique* and *proof* toward more open uses, such as *discovery*. If the expected results are not known when developing the conceptual model, then it is especially important to establish trust in the connection between the simulation model and the represented real-world system (McKelvey 2002). Therefore, simulations that are used for *discovery* or *prediction* require a larger effort to validate the simulation model.

P6. More open simulation uses require a higher validation effort to establish and justify the connection between the simulation model and the represented real-world system.

Johnson et al. (2014) provide a good example of a rigorous simulation development and validation process. It is a priori unknown what combination of mechanisms best explains the generative mechanisms underlying online communities. Therefore, the simulation is carefully developed, tested and tuned in an iterative process that employs multiple validation techniques and relies on purposefully collected real-world data.

Regarding the use of theories in simulation-based research in IS, our analysis demonstrates that theories easily translatable to a mathematical model, such as game theory or auction theory, are employed frequently in the extant literature. Nevertheless, owing to the non-deterministic and emergent nature of IS (Lyytinen and Newman 2008; Sabherwal et al. 2001), especially from a socio-technical perspective, we lack studies that develop the underlying conceptual model of a simulation as such. Hence, we encourage prospective research to take advantage of relevant change theories, such as the punctuated equilibrium theory, to reveal the *de facto* complexity of IS phenomena and to describe their inherent dynamics. Regarding the analyzed set of papers, in particular, agent-based simulations often employ a combination of multiple theories to describe individual components of the system or their relations, thereby providing a solid basis for constructing the underlying conceptual model of the simulation (Woodard and Clemons 2014).

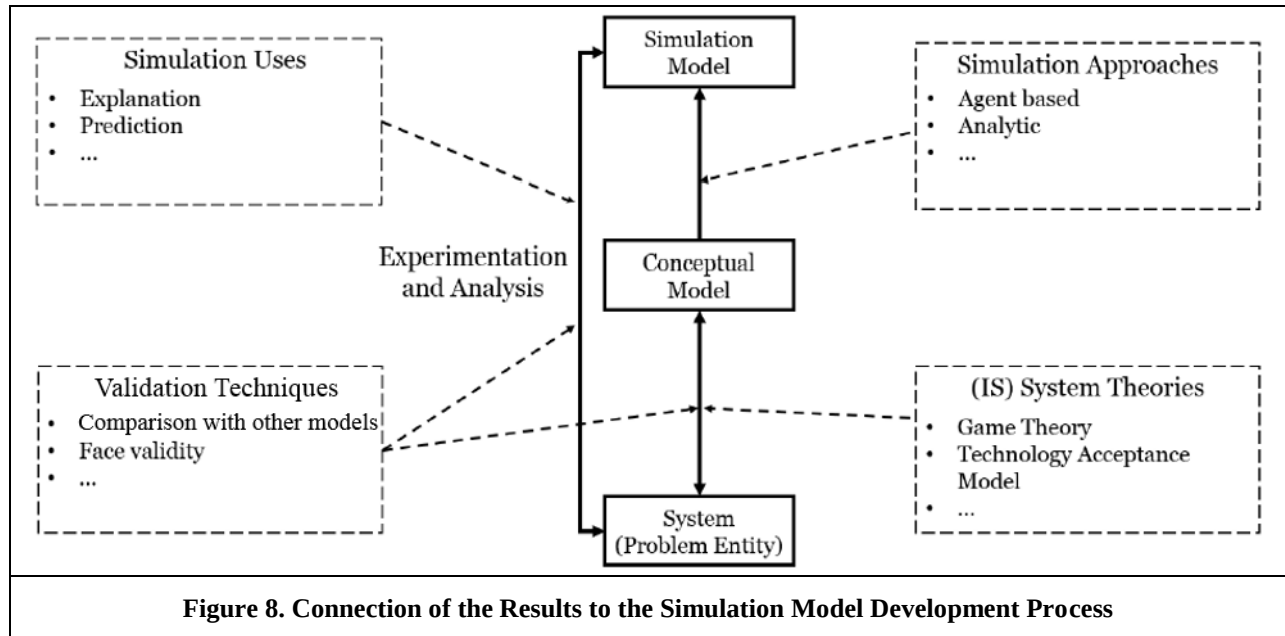
P7. The investigation of IS phenomena as socio-technical systems through simulation-based research is facilitated by the use of theories that conceptualize the non-deterministic nature and inherent dynamics of these phenomena.

Furthermore, simulation-based research has a recognized potential to contribute to theory testing and development in IS (Davis et al. 2007; Woodard and Clemons 2014) and in social sciences in general (Lazer et al. 2009). Translating constitutive elements of the extant theories into computational models allows researchers to test and refine these theories using a large volume of available data. This has been

rigorously demonstrated in Johnson et al.'s (2014) research on online communities, where four extant theories for generating mechanisms of power distributions in online communities are used to develop the simulation model. In turn, a series of simulation experiments is performed to test which generating mechanisms best mimic the behavior of a large dataset extracted from real-world online communities. The simulation experiments show that a multi-theoretic combination of all four generation mechanisms, operating concurrently, best explains the phenomenon. To achieve statistical significance, this result requires a large amount of data produced by careful experimentation and manipulation. Even though it would be unfeasible and potentially unethical to generate this data through real-world experiments, the use of simulation gave the opportunity to the authors to rigorously obtain this result.

The set of the 83 analyzed research papers is limited to the AIS Senior Scholar's Basket of Journals. More technical simulation-based research papers, which may be published in the *ACM* or *IEEE* transactions, are not included in this study. Furthermore, our focus is on an understanding of what has been done in IS research and we only briefly touch on what could be done in the context of simulation model validation, as suggested by Sargent (Sargent 2005), in proposition P5. There is potentially more insight to be gained from including methodological research from other areas in which simulation research is more mature.

Nevertheless, due to the particular difficulties arising from the socio-technical nature of IS research, we believe our analysis of the status quo to be useful for future simulation-based research. The results facilitate the conceptualization of socio-technical information systems for simulation model construction by giving researchers and practitioners an overview of publications that successfully managed to achieve this conceptualization. As Figure 7 shows, we analyzed relations along the entire process of simulation model development, not including the final technical step of implementing, i.e., coding, the actual simulation.



This allows anyone who is interested in building simulations in the IS context to start with a given research goal in a real-world information system and use this analysis to guide the way from the real-world problem entity to the simulation model. We describe, for each step of this process, those parts that are of common focus, including theories considered relevant, approaches to chosen simulations and, finally, those techniques currently employed to establish the connection between the resulting simulation model and the underlying real-world system.

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