Rethinking the Value of Simulation Methods in the Information Systems Research Field: A Call for Reconstructing Contribution for a Broader Audience

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Abstract

The impact of simulation methods for social research in the Information Systems (IS) research field remains low. A concern is our field is inadequately leveraging the unique strengths of simulation methods. Although this low impact is frequently attributed to methodological complexity, we offer an alternative explanation – the poor construction of research value. We argue a more intuitive value construction, better connected to the knowledge base, will facilitate increased value and broader appreciation. Meta-analysis of studies published in IS journals over the last decade evidences the low impact. To facilitate value construction, we synthesize four common types of simulation research contribution: Analyzer, Tester, Descriptor, and Theorizer. To illustrate, we employ the proposed typology to describe how each type of value is structured in simulation research and connect each type to instances from IS literature, thereby making these value types and their construction visible and readily accessible to the general IS community.

Keywords: Simulation methods, simulation in social sciences, research contribution, construction of knowledge, style of presentation

Introduction

The application of simulation research methods in the social sciences dates back over half a century to a computational analysis of organizational behaviors, pioneered by Cyert and his colleagues (Cyert and March 1963) at the Carnegie School (Burton and Obel 1995). Despite this long history, in contrast to its prominence in the natural sciences, the impact[1] of simulation in most social science disciplines remains low (Davis et al. 2007; Harrison et al. 2007). The employment of simulation methods[2] is particularly

[1] By 'impact' we mean the *perceived* research value from, consequent extent of citation of, and ultimately, extent of employment of, simulation research methods. A premise of this paper is that infrequent adoption of simulation is due to its low impact, and thus the focus is on analyzing the cause of its low impact.

[2] In this paper, our consideration is strictly scoped to simulation methods for social research in the IS research field. By social research, we mean research dealing with human (individuals and collectives) phenomena often in those fields such as Anthropology,

scarce in the Information Systems (IS) research field, rarely endorsed by researchers to investigate core social behavioral issues of the field such as the implementation, adoption, and use of IS. Our concern is the IS research community is inadequately leveraging the unique strengths of simulation methods and is not embracing methodological diversity (Robey 1996; Benbasat and Weber 1996).

To promote simulation methods in the social sciences and to encourage their broader adoption, several writings have focused on clarifying their rationale (Burton and Obel 2011; Harrison et al. 2007; Anderson 1999; Anderson et al. 1999; Carley 2009). Others have emphasized improving practices of simulation in social research (e.g. developing prescriptive procedures and analytic techniques) (Davis et al. 2007; Carley 1996; Burton and Obel 1995).

Almost all previous such work relies on a premise that, the low attraction of simulation is attributed to the methodological complexities of simulation. However, in this paper, we offer an alternative explanation of the low take-up of simulation methods by social scientists – the poor "value construction" in simulation research. Arguably, this explanation can also fully explain the current state of simulation research and, more importantly, points to actionable advice that simulation researchers might take to proactively seek to broaden their target research audiences.

We refer to "value construction" as the construction of scientific research contribution in order to advance knowledge. Several IS researchers have broached the issue of research contribution. For instance, Mathiassen et al. (2012) suggest, that Action Research publications should contribute to science or practice in "intended ways", and, therefore, how researchers structure their arguments in their publications must be in accord with whether or not research contributes as intended. Similarly, Gregor and Hevner (2013) highlight the importance of appropriately positioning and presenting Design Science research and note such effort can maximize the potential value of research.

Sharing similar concerns with Mathiassen et al. (2012) and Gregor and Hevner (2013), we particularly focus on how the studies employing simulation methods structure their contribution to knowledge. By mindfully denoting "construction" of research value or scientific contribution, we pay particular attention to how research contribution advances the existing knowledge base, understanding of which is rooted in the social constructivist view suggesting that knowledge cannot be known without involving the knower (Guba and Lincoln 1985). Whether or not one research contribution should be counted as new knowledge depends on whether the contribution is meaningful to a community of researchers and whether it meets the standards that define legitimate knowledge. These standards are (often implicitly) shared among the community of researchers for which the contribution is intended.

As such, researchers' efforts with manufacturing new knowledge in attempting to meet these shared standards might be conceived as the construction of knowledge (Locke and Golden-Biddle 1997). The term "construction" highlights the process whereby new knowledge is derived from and built upon the established, pre-existential knowledge base. A similar view on the construction of knowledge is conveyed by Weick (1989), who emphasizes that the value of theory does not lie in validating "truth" but in offering speculations not previously suspected.

In light of this view, scientific research findings are said to be of little value unless they are structured in a manner that reveals their importance to target research communities and established upon the accepted knowledge of related fields (Locke and Golden-Biddle 1997). Though the studies employing simulation methods typically generate findings in forms that are intuitive to the mindsets of simulation modelers (e.g. an implicit algorithmic-like "IF-THEN" form), these forms may not be meaningful and accessible to the mindsets of the researchers trained in other social science methods (e.g. case research and survey research). More importantly, they may fail to make connections to the relevant knowledge base outside their own respective fields.

A belief underlying the current paper is that a more intuitive value construction from simulation research, better connected to the knowledge base, may facilitate increased value and broader appreciation of simulation research, and wider adoption in the IS research field. Motivated by this belief, we first survey

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Psychology, Sociology, and their applied fields (Orlikowski and Baroudi 1991). Hereinafter, without qualification, 'simulation' refers to simulation for social research and 'simulation research' refers to social research applying simulation research methods.

simulation studies published in nine well regarded IS journals over the last decade (2004 - 2013) and then conduct a meta-analysis of the surveyed studies, evidencing low impact of simulation research. To further facilitate better construction of contribution in simulation research, we propose a typology of simulation research contribution. Drawing from the literature addressing purposes of computational models, we synthesize these purposes and typify four most common types of simulation research contribution: (I) *Analyzer*, (II) *Tester*, (III) *Descriptor*, and (IV) *Theorizer*. For each type, we describe its structure regarding how value is constructed and connect the structure to instances from the surveyed studies.

This paper contributes to the research field in several respects. It elucidates common contributions from simulation studies and makes these contributions and their construction visible and readily accessible to the general IS research community. The value of computational models has previously been reported in several places (e.g. Burton and Obel 1995; Carley 2009). However, an in-depth, focused consideration on value construction and its empirical analysis have not been addressed. Our analysis thus offers further insights into how value is structurally composed in simulation research practice.

Further, this paper may be of value to simulation researchers, in attuning them to the importance of value construction in simulation research, and in explicating alternative ways of value construction to broaden the audience of research. Several useful remedies are distilled from insights gained. These remedies may aid future simulation researchers in better thinking about, structuring, and presenting their research.

It is hoped, our discussion would initiate a continuing dialogue amongst simulation research practitioners and methodologists. Our aim is to improve the quality of simulation research value construction and to stimulate broader debate in the IS field on its importance.

The rest of this paper is organized as follows. The next section briefly introduces simulation methods and computational modeling for social research. Subsequently, we further elaborate the perceived low impact of simulation research in the IS field and analyze the potential underlying reasons for its minor influence. We next empirically assess the impact of simulation research in IS through surveying the literature. To aid the analysis of value construction in simulation research, we synthesize previous piecemeal thought on the purposes of computational modeling and derive four common simulation research contribution types. Based on this organizing framework, a qualitative, descriptive case-analysis strategy is employed to flesh out the structures of value construction in the surveyed studies. We conclude with implications.

Overview of Simulation Research Methods

Before we proceed to an in-depth analysis, we overview some basic concepts and rationale of simulation. Notably, a comprehensive review of simulation methods in social sciences is not the aim, exemplars of which appear in previous literature (see Harrison et al. 2007; Anderson 1999).

Simulation methods use "computer software to model the operation of 'real-world' processes, systems, or events" (Davis et al. 2007, p. 481). One distinctive feature of simulation methods is that, the model employed, referred to as a *computational model* (Carley 2009), is often represented in the form of computer code. Notably, whether or not a simulation study needs to develop a 'new' computational model depends on the purpose of the study. That is, a new computational model is not necessarily the research aim. In fact, several researchers explicitly argue, that for certain purposes such as theory building, developing a new computational model *per se* does *not* make a useful contribution to knowledge (e.g. Davis et al. 2007). This view may be particularly confusing to researchers in the positivist research tradition, whose aims typically are to develop new variance or process models. The use of computational models is more flexible than explaining phenomena (as typically is the goal with variance or process models). One of our aims is to elucidate such differences.

At its core, a computational model embodies a set of algorithms that can be executed by computers. This set of algorithms is the logic of a model, which is often translated from a formally specified, mathematical model, typically consisting of variables, equations specifying the relationships among the variables, and transition rules specifying the changing patterns of variable states from one time to another (Harrison et al. 2007). *Running a computational model* refers to executing the algorithms on a computer, whereby the computer calculates the end-state values of variables according to the beginning-state values of variables and the specified equations and transition rules in the computational model. The end-state values of variables are often called *model output*, whereas the beginning-state values of variables are often called *model input* or *model parameters*. Furthermore, to investigate social issues, the formal, mathematical model underlying a computational model needs to characterize some real-world systems, the symbolic representation of which is commonly known as a *conceptual representation* or a *conceptual model* (Davis et al. 2007).

Computational models can be *deterministic* or *stochastic*. Given fixed model parameters, a deterministic model generates the exact same model output each time it is run. Output of a stochastic model may vary given they include random intermediate variables, the values of which are not explicitly specified. Rather, these values are randomly generated each time the model is run, according to pre-determined distribution patterns (such as a Normal distribution).

Further, computational models can be developed following specific conceptual modeling approaches. Such approaches emphasize specific aspects of reality and related constraints, an example being *agent-based models* that focus on modeling interactions among entities. Common conceptual modeling approaches include[3] *agent-based modeling* (also *multi-agent systems*), *systems dynamics*, and *cellular automata* (Anderson 1999).

Employing simulation methods often involves computational experimentation. Given real-world systems are subject to random disturbances, most computational models (particularly those that are used to investigate social issues) are stochastic. As such, to capture reliable patterns of model output, running a computational model often requires a repeated design. Put it differently, a computational model is run multiple times for a given set of model parameters to measure the distribution of model output. Each simulation execution is analogous to a single observation in laboratory experimentation.

Therefore, *computational experimentation* can be understood as the running of a computational model according to a predetermined experimental design (such as a simple factorial design) (Law and Kelton 1991). The experimental environment is the computing device executing the computer algorithms. Through the computational experiments, factorial effects are artificially created through adjusting model parameter values, where a combination of model parameter values is assumed to be representative of a real-world population.

Thus, the development of computational models is often done in order to carry out computational experiments (Davis et al. 2007). This is the main reason why computational modeling per se may only be and often is considered as an intermediate research effort, rather than the research finding. However, a computational model could be both intermediate research effort and the ultimate outcome.

Studies employing simulation methods have two main distinctive strengths. Given that a computational model is clear and unambiguous in characterizing real-world events and processes, simulation methods have the merit of clarity, ease of comparability, and logical power[4] (Harrison et al. 2007). The second merit is related to the tractability of a computational model (Anderson 1999). When simulation methods are employed, complex real-world processes can be modelled and subsequently decomposed into step-by-step calculations. With modern computers, the predicted effects of these complex processes can have numerical solutions. Conversely, non-computational mathematical models or other linear models (e.g. most variance-based models) suffer from limited tractability; that is, most cannot deal with nonlinear, often analytically unsolvable problems, which are prevalent in the real world (Anderson 1999).

Given their strengths, simulation methods can complement other social science research methods. For instance, agent-based modeling can capture emergent phenomena in complex systems, provide natural and intuitive descriptions of phenomena, and flexibly control variables in computational experiments (Bonabeau 2002). Such strengths can overcome methodological limitation prevalent in other methods, through uncovering analytical blind spots due to, for example, methodological myopia and biases (e.g. ambiguous theory description and imperfect control over experiments or field settings) (Burton and Obel 2011; Carley 1996; Davis et al. 2007).

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[3] We acknowledge that there are other modeling approaches, such as discrete-event simulation, that are not addressed here. Given the scope limitation of this work and our own experiences with IS research, we emphasize the listed three modeling approaches as typical simulation modeling approaches in the IS research field.

[4] Computational models rarely contain errors in logical reasoning; such errors are relatively easy to be identified by readers.

Focusing on Increasing the Impact of Simulation Research

Although the strengths of simulation methods are tangible, simulation studies seemingly have achieved limited impact in the IS field. Orlikowski and Baroudi (1991) found that over 90% of IS research employed one of three dominant research methods – case studies, laboratory experiments, or surveys. A later study found the representation of these three methods in IS had increased to about 95% (Chen and Hirschheim 2004). The dearth of simulation studies suggests the approach is not well regarded in IS.

The literature suggests a main reason for the limited impact of simulation studies is their methodological complexity; specifically, the rationale for simulation is not easily discernable by most social scientists untrained in simulation methods (Harrison et al. 2007; Anderson 1999; Anderson et al. 1999). It would thus seem to follow that improved understanding of simulation methods will encourage more researchers to become both producers and consumers of simulation research (Harrison et al. 2007). This belief has stimulated several recent attempts to clarify both the rationale for simulation, as well as its potential applications to social research problems (e.g. Burton and Obel 2011; Harrison et al. 2007; Anderson 1999; Carley 2009).

However, the methodological complexity argument seemingly puts all the blame on the research audience (i.e. their inability to understand), offering limited actionable advice that simulation researchers might adopt to proactively improve their work. On the other hand, the literature includes exemplary simulation studies that have attracted extensive attention; suggesting simulation research can be influential. The seminal Garbage Can Model (Cohen et al. 1972) is one such example. Perhaps these exemplars suggest generalizable success factors that may be emulated to help simulation researchers improve their work and broaden their research audiences.

We suggest a good value construction practice is such a key success factor. Therefore, an alternative explanation might be, that simulation researchers' consistently poor value construction is constraining their research impact. This alternative explanation is inspired by recent discourses regarding the construction of knowledge in Management (e.g. Alvesson and Sandberg 2011; Sandberg and Alversson 2011) and regarding positioning and presenting research findings in the IS field (Mathiassen et al. 2012; Gregor and Hevner 2013). Specifically, Mathiassen et al. (2012) argue the style of presenting research matters, in terms of advancing knowledge to enlighten academicians and professionals in "intended ways". A similar thought is conveyed by Gregor and Hevner (2013), who advocate for positioning and presenting design science research, emphasizing appropriate production and consumption of science.

Yet, the construction of knowledge is not as intuitive and straightforward as it may seem, as an idea only becomes a contribution to the knowledge base "when it is constructed as important by the members of a scholarly community, relative to the accepted knowledge constituted by the field's written work" (Locke and Golden-Biddle 1997, p. 1025). That is, in order to attract a broader audience, simulation research contribution should not only be meaningful to simulation modelers, but, more importantly, should also channel key ideas based on accepted knowledge and research practice of the general research community.

This begs the question: to what extent is this achieved in current simulation research? Our concern and speculation is, not too much. One possible cause is that simulation studies often put much emphasis on presenting research findings (such as crafting complex data representation diagrams) with less emphasis on formulating contribution. Simulation findings are typically organized in a mechanical fashion, often as algorithmic-like "IF-THEN" statements (e.g. if the value of a is 0.5, then b will increase), where variables in the results are mechanically replaced by variable names. Such statements are equated with research contribution without connecting to the knowledge base of the general research community. This, however, may be problematic because; as acknowledged by several simulation modelers (e.g. Burton and Obel 1995; Carley 2009), the purpose of computational modeling varies from one study to another. A standard, mechanical style of organizing research findings may thus mask potentially differing types of research contribution. Without the connection between the contribution and the intended knowledge base, it is extremely difficult for researchers, particularly those lacking simulation and computational modeling experience, to understand the contribution let alone become active consumers of simulation studies.

Our analysis highlights the need for in-depth understanding of how value or contribution is and should be constructed in simulation research. Before proceeding with analysis of value construction, we survey a sample of simulation studies in IS, aiming to (1) assess the historical impact of simulation research, and (2) provide instances to assist in thinking about and substantiating the analysis of value construction.

Methodology

To prepare a sample of simulation studies in the IS, we surveyed articles published in nine prestigious IS journals over the last decade (2004-2013). The eight *Senior Scholars' Basket of Journals* endorsed by the Association for Information Systems as high quality journals in the IS discipline, were selected: *MIS Quarterly* (MISQ), *Information Systems Research* (ISR), *Journal of Management Information Systems* (JMIS), *European Journal of Information Systems* (EJIS), *Information Systems Journal* (ISJ), *Journal of the Association for Information Systems* (JAIS)[5], *Journal of Information Technology* (JIT), and *Journal of Strategic Information Systems* (JSIS). *Information & Management* (I&M) was also included given its high quality (as in the *Excellence in Research for Australia 2010 Journal Ranking List*, I&M is ranked at the highest-quality "A*" level) and its high receptivity to social research in IS. A combination of keywords (including "simulation", "computational model*", "computer model*", "agent-based", "multi-agent", and "system dynamics") was adopted, to search the "topic" field of an article (i.e. the title, the abstract, and the keywords provided by the author(s) and generated by the database) through the *Web of Science* database. The initial search yielded 67 hits.

Many of these articles did not refer to simulation as a research method, or did not use simulation methods for social research. To exclude irrelevant articles, a manual screening process was performed. Consistent with Harrison et al. (2007), articles were removed from the final dataset if (1) simulation in the article was used for implementing a part of or the whole of some IT artifact, such as an agile manufacturing system (e.g. Yu and Krishnan 2004), or a decision-support system (e.g. Lee and Kwon 2006; Nissen and Sengupta 2006; Vahidov and Fazlollahi 2004); (2) the term "simulation" (or other searched terms) was used in the article to describe the IT artifact investigated in behavioral research (i.e. simulation was not the research method), such as describing simulation-based technology/software (e.g. Rincon et al. 2005); (3) the research in the article did not address social phenomena (i.e. not involving human phenomena), such as using simulation to evaluate the performance of IT artifacts, such as statistical analysis algorithms (e.g. Goodhue et al. 2007; Qureshi and Compeau 2009) or an IT system that supports problem solving (e.g. Muller-Wienbergen et al. 2011); or (4) the article was not a conventional research article, but rather is a comment, reply, or alike (e.g. Tallis and Aleksander 2008). A total of 25 articles were retained after screening (Table 1).

Meta-Analysis of Simulation Studies in IS

Table 1 illustrates the count of studies across the sample journals and years.

#	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	Total.
MISQ	0	1	0	0	0	0	0	1	0	0	*2*
ISR	2	0	0	0	1	2	3	2	1	0	*11*
JMIS	0	1	1	1	1	0	1	0	0	0	*5*
JAIS	NA	NA	0	0	0	2	0	0	0	0	*2*
JSIS	0	0	0	0	0	0	0	1	0	0	*1*
EJIS	0	0	0	0	0	1	0	0	0	0	*1*
JIT	0	0	1	0	0	0	0	0	0	0	*1*
ISJ	0	0	0	0	0	0	0	0	0	0	*0*
I&M	0	0	0	1	0	0	0	1	0	0	*2*
Total.	*2*	*2*	*2*	*2*	*2*	*5*	*4*	*5*	*1*	*0*	*25*

Table 1. Study Counts, by Journal and Year

[5] For JAIS, we included only 2006 to 2013 given that previous years of this journal were not indexed in the *Web of Science* database.

As previously speculated, the number of social studies applying a simulation method is small (i.e. 25 out of over 3400 articles). In most years of most journals, there are no such studies published (71 greyed cells in Table 1 of 88 cells). Given the limited data, no clear publication trend is discerned, though there appears to have been a small increase from 2009 to 2011, with a drop-off in 2012 and zero studies in 2013. The number of studies varies much across journals; *ISR*, publishing the most (11) followed by *JMIS* (5), these two journals seemingly somewhat more receptive to simulation studies than other sampled journals (none of which published more than 2 in the ten year period). Even *ISR*, with 11 studies, has averaged only just over 1 such study per year, 9 of these 11 occurring in 5 of the 10 years.

To gauge the impact of these simulation studies, their citation counts were obtained from *Web of Science* (Table 2). Citation count ("#" in Table 2) is one of the most commonly used indicators to evaluate the impact of studies (Walstrom and Leonard 2000). The citation count was further divided by elapsed years since publication (denoted as "#/yr" in Table 2). Given the average number of citations per article does differ by journal and is also influenced by the recency of studies, we computed a benchmark citation value ("BM#" in Table 2) for each study; defined as the average citation count of all studies published in that journal in the year in which the focal study was published[6]. Based on the benchmark citation values, we calculated a normalized citation value ("NM%" in Table 2) through calculating the increment (positive) or decrement (negative) proportion of the citation counts (#) in comparison to the benchmark values (BM#)[7]. The normalized citation value usefully compares the citation frequency of the focal study, with the average citation frequency of other studies published in that journal in that year.

<table>
<tr><th>Study Rank</th><th>#</th><th>#/yr</th><th>BM#</th><th>NM%</th><th>Study Rank</th><th>#</th><th>#/yr</th><th>BM#</th><th>NM%</th></tr>
<tr><td>1. Chen and Edgington 2005</td><td>38</td><td>4.75</td><td>113.20</td><td>-66%</td><td>14. Kwon et al. 2007</td><td>4</td><td>0.67</td><td>18.15</td><td>-78%</td></tr>
<tr><td>2. Bampo et al. 2008</td><td>33</td><td>6.60</td><td>24.61</td><td>34%</td><td>15. Wang et al. 2011</td><td>3</td><td>1.50</td><td>3.74</td><td>-20%</td></tr>
<tr><td>3. Curseu 2006</td><td>25</td><td>3.57</td><td>14.23</td><td>76%</td><td>16. Chang et al. 2010</td><td>3</td><td>1.00</td><td>8.00</td><td>-63%</td></tr>
<tr><td>4. Dutta and Roy 2005</td><td>18</td><td>2.25</td><td>28.49</td><td>-37%</td><td>17. Das et al. 2011</td><td>2</td><td>1.00</td><td>4.43</td><td>-55%</td></tr>
<tr><td>5. Chen et al. 2007</td><td>15</td><td>2.50</td><td>26.98</td><td>-44%</td><td>18. Choi et al. 2010</td><td>2</td><td>0.67</td><td>5.25</td><td>-62%</td></tr>
<tr><td>6. Kumar et al. 2008</td><td>13</td><td>2.60</td><td>16.87</td><td>-23%</td><td>19. Port and Bui 2009</td><td>2</td><td>0.50</td><td>7.79</td><td>-74%</td></tr>
<tr><td>7. Jones et al. 2006</td><td>9</td><td>1.29</td><td>23.56</td><td>-62%</td><td>20. Adomavicius et al. 2009</td><td>1</td><td>0.25</td><td>19.39</td><td>-95%</td></tr>
<tr><td>8. Chiang and Mookerjee 2004</td><td>9</td><td>1.00</td><td>74.86</td><td>-88%</td><td>21. Guo et al. 2012</td><td rowspan="5">0</td><td rowspan="5">0.00</td><td>2.23</td><td rowspan="5">-100%</td></tr>
<tr><td>9. Nan 2011</td><td>7</td><td>3.50</td><td>10.89</td><td>-36%</td><td>22. Gupta et al. 2011</td><td>4.43</td></tr>
<tr><td>10. Raghu et al. 2004</td><td>7</td><td>0.78</td><td>74.86</td><td>-91%</td><td>23. Adler et al. 2011</td><td>4.20</td></tr>
<tr><td>11. Walden and Rrowne 2009</td><td>6</td><td>1.50</td><td>9.53</td><td>-37%</td><td>24. Ba et al. 2010</td><td>8.00</td></tr>
<tr><td>12. Greenwald et al. 2010</td><td>5</td><td>1.67</td><td>8.00</td><td>-38%</td><td>25. Nan and Johnston 2009</td><td>9.53</td></tr>
<tr><td>13. Sen et al. 2009</td><td>5</td><td>1.25</td><td>19.39</td><td>-74%</td><td colspan="5"></td></tr>
</table>

Table 2. Study Citations, Ranked

[6] E.g. BM# (for *MISQ*, 2005) = (citation count of Study 1 published on *MISQ* in 2005, +...+ citation count of Study *N* published on *MISQ* in 2005) / *N*, where *N* is the total number of articles published on MISQ in 2005.

[7] For instance, for the 1st listed study (Chen and Edginton (2005)), the NM% is (38-113.20)/113.20 ≈ -66%.

Table 2 suggests that, not only is the total number of simulation studies low (as indicated in Table 1), but also the number of citations of most simulation studies is comparatively lower than the average. The most cited study received 38 citations. Five studies had no citations. Based on average citations per year, the most cited study is cited an average of 6.60 times per year, whereas slightly over a half (i.e. 13 out of 25) of the studies is cited no more than once per year. More importantly, except for two studies, the second study (Bampo et al. 2008) and the third study (Curseu 2006), most studies (i.e. 23 out of 25) have at least 20% fewer citations (indicated by the negative percentage in the "NM%" column of Table 2) than the average (the BM#). These descriptive statistics jointly suggest that simulation research is of relatively low impact[8] in the IS discipline.

Construction of Simulation Research Contribution

To facilitate a deeper understanding of value construction in simulation studies, and thereafter to offer tentative advice on how contributions might be better constructed to inform a broader audience, we developed a typology, consisting of the most common types of simulation research contribution.

Rather than explicitly addressing research contributions, the methodological literature on simulation instead focuses on the 'purposes' of a computational model. We assume these purposes are often fully realized and therefore equate these with the realized value from simulation studies. Table 3 summarizes several most common purposes of a computational model, derived from the literature.

Burton and Obel (1995): (1) Description of the behavior; (2) Advice or normative model; (3) Training; (4) Hypothesis testing; (5) Exploration; (6) Theory generation; and (7) Alternative explanations of the phenomenon.
Carley (2009): (1) Test bed for new ideas; (2) Predict impact of technology or policy; (3) Develop theory; (4) Determine necessity of a posited mechanism; (5) Decision making aids; (6) Forecast future directions; (7) What if training tools; (8) Suggest critical experiments; (9) Suggest critical items for surveys; (10) Suggest relative impact of different variables (factors); (11) Suggest limits to statistical tests for non-linear systems; (12) Substitute for person, group, tool, etc. in an experiment; and (13) Hypotheses generators.
Axtell (2000): (1) Check the correctness of numerical solutions of equations; (2) Compute approximate value for analytically unsolvable problems; (3) Present mathematical results; (4) Complementary to pure mathematical theorizing; and (5) Substitute for analysis in completely intractable problems.
Carley (1996): (1) Engineering or emulation models to provide explicit advice to a particular corporation or on specific problem; and (2) Intellective models to show proof of concept or to illustrate the relative impact of basic explanatory mechanisms.
Burton and Obel (2011): (1) Models for answering what-is questions: a description and explanation; (2) Models for answering what-might-be questions: an examination of variations, alternatives, and exploring possibilities and boundaries; and (3) Models for answering what-should-be questions: the choice of which is best among alternatives.

Table 3. Summary of Common Purposes of Computational Model

Based on these purposes of a computational model, we synthesized and distilled four most common types of simulation research contribution (summarized in Table 4): (I) *Analyzer*, (II) *Tester*, (III) *Descriptor*, and (IV) *Theorizer*. These four contribution types are distinctive in terms of their respective structure of value construction, and their corresponding realized computational model purpose.

Notably, the value of scientific research varies, and what constitutes a contribution to knowledge is in flux and can be perceived differently from one researcher to another (Whetten 1989). It is not possible to exhaustively consider every potential contribution form and value of research. Therefore, we do not claim our identified types are comprehensive or exhaustive.

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[8] Is either ill-understood or perceived as of little value or relevance and thus is not cited.

Further, to suffice as contributions, these purposes of a computational model must align with the existing knowledge base, thereby, representing the value connected to the established knowledge of related fields (Locke and Golden-Biddle 1997). At a high level, different theory types can be viewed as commonly understood knowledge types in a field. In IS, Gregor's (2006) taxonomy of IS theory types is perhaps most comprehensive. Table 4 further cross-references each of the four contribution types with each of Gregor's five theory types, representing their potential high-level links with the established knowledge base.

Type	Contribute To…	Key Ref^	IS Theory Type*					#	%
			A	P	E	EP	DA		
I. Analyzer	Predicting what will happen when certain conditions are met or providing prescriptions predictive of future outcomes;	[a, b, d, e]		✗			✗	14	56%
II. Tester	Logically deducing or empirically testing statements of relationships among constructs, or statements about certain predictions;	[a, b, c]		✗		✗	✗	3	12%
III. Descriptor	Providing description of the phenomena of interest and/or explanations regarding what is, how, why, when, and where;	[a, c, d, e]	✗	✗	✗	✗	✗	9	36%
IV. Theorizer	Providing description of the phenomena and formulating theoretical statements about the described phenomena;	[e, f, g]		✗	✗	✗		3	12%
Total.	-	-	-					29	116%

^Reference: [a]=Burton and Obel 1995, [b]=Carley 2009, [c]=Axtell 2000, [d]=Carley 1996, [e]=Burton and Obel 2011, [f]=Davis et al. 2007, [g]=Harrison et al. 2007.

*A=Analytic, P=Prediction, E=Explanation, EP=Explanation and Prediction, DA=Design and Action.

Table 4. A Typology of Simulation Research Contribution

Each contribution type in Table 4 is further illustrated in the following subsections respectively. Note that not every model purpose (e.g. in Table 3) is subsumed by the four contribution types listed (Table 4). For instance, computational models for training purposes (Burton and Obel 1996; Carley 2009) do not deal with social research issues; thus, are not a focus. "Exploration" type models (Burton and Obel 1996; Carley 2009) are overly general and also excluded. The model purpose type "alternative explanations of the phenomenon" (Burton and Obel 1996) is excluded, as these purposes are considered in both the "Theorizer" and the "Descriptor" types. Other types of model purposes, such as models for computing mathematical solutions and models for presenting results (Axtell 2000) are excluded, since they are only representative of intermediate values but do not capture the final cause or the exact contribution to knowledge, the criterion of which is suggested and adopted by Gregor (2006). We repeat, we do not claim the identified types are exhaustive or mutually exclusive, as we intend to develop a typology, instead of a classification scheme. As elucidated by Doty and Glick (1994), a typology focuses on empirical predication of instances, whereas a classification scheme is concerned with discriminating objects into exhaustive and mutually exclusive categories to the extent possible.

To investigate how contribution is constructed in previous simulation studies, we employed these four identified contribution types as an organizing framework and conducted a detailed qualitative analysis of the sampled studies. Each study was viewed as a single case, for which the investigators' practice of constructing knowledge was analyzed and reported. The analysis approach followed is consistent with that of Brown and Eisenhardt (1997) and Eisenhardt (1989).

The count of each contribution type instance in the sampled studies is summarized in Table 4. The total count (i.e. 29) is greater than the total number of studies (i.e. 25), as a single study may yield multiple types of contribution. Table 4 suggests the most frequently reported contribution type (i.e. 56%) is the Analyzer type, implying that either the needs of practice (e.g. considering policies) are of primary concern to simulation researchers, or that simulation research is more likely to yield this type of contribution. Further, the contribution instances are unequally distributed, with the Tester type and the Theorizer type representing substantively smaller proportions (i.e. both 12%) than the other two types (i.e. 36% and 56% respectively). Concomitantly, we believe the increased emphasis in theory development and theory testing in the IS field (Markus and Sanders 2007; Weber 2003) may suggest the Tester and Theorizer types can be of greater interest to the broader IS social research community. Therefore, the call is thus for increased Tester and Theorizer types of contribution from IS simulation researchers. Increasing Tester and Theorizer types is not only possible, but ideal for studies applying simulation methods. As will be further argued in subsequent sections, studies that make a Descriptor type contribution can potentially be further extended to make other types of contribution. This implies that, 36% of sampled studies (Type III in Table 4) might potentially be extended to increase contribution. Though the challenge of such extension remains, the potential appears promising.

Type I: Analyzer

14 studies fall into the Analyzer contribution type. When this contribution is claimed, the studies often suggest their usefulness to senior managers in decision making or to regulators in policy design. These studies could explicitly predict what will happen when certain conditions are met or certain scenarios are encountered, and/or offer prescriptive advice, implicitly predictive of future events and outcomes (i.e. the decisions or policies are expected to be implemented). This type of contribution is well aligned with *Theory for Prediction* and *Theory for Design and Action* in Gregor's (2006) taxonomy of IS theory. For Theory for Prediction predictive power is a concern, whereas Theory for Design and Action, as the name implied, offers normative prescriptions (Gregor 2006). Therefore, for studies contributing to this type, stronger predictive power is also an explicitly argued strength, in comparison to previous research.

This type of contribution is often organized as: first relate the computational model to a general or specific decision-making problem or policy design need, and then describe recreated scenarios characterized by the computational model. The researchers often formulate the contribution to emphasize interesting or novel scenarios analyzed, and/or to point out deficiencies and limitations through comparison with prior analysis of identical scenarios; thereby making a contribution through informing better decision making or better policy design. Consider the following scripts, with attention to how the model is connected to practical scenarios and how the desirable strategies, as a result of the studies, are highlighted.

> In exploring **the impact** that social network structures **have on campaign dynamics**, we have provided managers with useful approaches for **optimising the success of a viral campaign**. Specifically, our contributions are threefold. First, we propose a conceptual framework for digital social networks [...] Second, we illustrate the impact [...] on campaign performance. [...] Third, [...] quantifying the impact of campaign management inputs and [...] for **managerial decision making**. (Bampo et al. 2008, p. 288, emphasis added)
>
> It employs a modeling approach that is based on system dynamics, **permitting managers to explore the implications of alternative decisions when** seeking to adopt and implement SOA. [...] By carefully integrating the two models from different levels, we were able to **examine the consequences** of an organization's decision to adopt SOA **in the context of** the large picture of industry-wide diffusion. (Choi et al. 2010, p. 281-282, emphasis added)

The above two studies argue contingent usefulness of multiple alternative strategies (of decision-making). That is, there is no globally optimal (i.e. only regionally optimal) strategy. In contrast, claiming this type of contribution may choose to compare alternative strategies and thereby flesh out the ostensibly more appealing one for certain scenarios. In this way, the studies emphasize analyzing one optimal strategy, instead of multiple alternative strategies. Studies presenting contribution in this manner often imply the optimal strategy is novel and interesting and is thus superior to those previously reported. Consider the following scripts and note how the superior strategy is emphasized.

> An analytical model is presented and **evaluated for effectiveness of a proposed** dynamic priority-based **pricing scheme vis-à-vis a baseline** fixed-price single-quality level SLA. […] the proposed dynamic pricing scheme **is likely to be more effective than** a fixed-price approach from a system welfare perspective. (Sen et al. 2009, p. 258, emphasis added)

> The simulation is used to **highlight** the benefits of **mixed approaches**. Our methodological discussion provides the necessary **basis** to enable the **practitioner to make use of** whichever of the multitude of methods and processes that are most suitable **in their particular context**. (Port and Bui 2009, p. 318, emphasis added)

> The **purpose** of this research is to establish **a simulation model of global supply chain** […] to prove that **the implementation of RFID system can best improve** the inventory cost effectiveness. (Wang et al. 2011, p. 308, emphasis added)

Improving the efficiency and effectiveness of policies is also prevalent in arguing this type of contribution. Policies can be conceived as consisting of complex, systematic sets of simple decision-making dimensions. Consider the following examples.

> Even though […], some of **the insights** gained from our analysis are useful in **understanding the implications under other revelation policies** as well. (Greenwald et al. 2010, p. 34, emphasis added)

> Simulation experiments **reveal** that **the fault threshold policy can be applied** even if several homogeneity assumptions in the model are relaxed, **allowing for** […] **the fault threshold policy outperforms a fixed-release policy** in which system integration occurs whenever a fixed number of modules has been released. (Chiang and Mookerjee 2004, p. 3, emphasis added)

> We aim to investigate **how various market design factors** including […] **affect** computational market efficiency […] this study **complements the previous BTM framework** in several ways, chiefly by **enabling** several characteristics used by actual agents **in real-world decision making**. (Guo et al. 2012, p. 825, emphasis added)

The Analyzer type of contribution is and continues to be the most important type of research contribution derived from simulation research. The prevalence of this type of contribution is closely related to the core strengths of simulation methods. That is, simulation methods are often suitable for answering what-might-be questions in contrast to other social research methods such as case studies or surveys (Burton and Obel 2011). Simulation modeling facilitates experimentation with practical scenarios that cannot be easily recreated or experienced in the real world. Such experiments are conducted in a contained virtual environment with little cost. Therefore, the research findings from experiments are often well aligned with practical concerns with what might happen given certain speculated or mimicked scenarios.

Though some simulation studies are highly specialized for generating this type of contribution, they could be extended to derive other types of contribution. Consider the following scripts, where only the Analyzer type of contribution is constructed in the study, but we believe the study could have simultaneously addressed other types of contribution.

> Our model provides **insights into complex decision making with regard to KC process investments**. We **demonstrate** that task, worker competency, and knowledge depreciation **are all relevant** variables, **in addition to** measurable costs, in determining the optimal choice for organizational value. […] Our model provides a contribution, as one of the first to **quantify the decision criteria** required by managers and knowledge workers with regard to knowledge creation process investment decisions using organizational and economic theory. (Chen and Edgington 2005, p. 305-306, emphasis added)

In the above scripts, the Analyzer contribution is clearly formulated. It may be possible, for example, to further bridge the simulation modeling and analysis result to the IT business value research literature (Kohli and Grover 2008; Melville et al. 2004) and to demonstrate how the simulated value creation mechanisms might inform future IT business value research; in terms of better (more realistically) theorizing practical scenarios thus improving internal coherence, better conceptualization of key intermediate constructs that may potentially be dismissed in value creation processes, and better measurement of constructs in practical settings.

Type II: Tester

The second type of contribution, Tester, is reported in 3 studies. To make this type of contribution, the studies need to focus on testing hypotheses using simulation methods. The hypotheses could explain statements about relationships among constructs, or be more general kinds of hypotheses about predicted effects of a strategy or a thing, such as a hypothesis predicting effectiveness of a policy.

The former kind of hypotheses begs empirical testing. To test such hypotheses, the researchers often use empirical data to set model parameter values in conducting computational experiments and subsequently test the hypotheses with generated output data (Burton and Obel 1995; Carley 2009; Axtell 2000). Such hypotheses are characterized as *Theory for Explanation and Prediction* in Gregor's (2006) taxonomy. As such, testing these hypotheses has value in the sense of falsifying or supporting IS Theory for Explanation and Prediction (Gregor 2006).

Unlike validating hypotheses through other research methods such as surveys or case studies, the latter kind of hypotheses can be tested without empirical data (or with). In example, the effectiveness of a policy is measured in the computational model, within which potential effects of the policy are logically deduced according to understanding of aspects of real-world processes of policy implementation. If empirical data are available, the data are often used as input to compute output and to further compare the effectiveness of the policy with certain standards such as the effectiveness of other commonly implemented policies. On the other hand, if empirical data are not available, the legitimacy of testing hypotheses often depends on premised empirical values and distributions of model input. That is, if the premises are strong and more likely to be realistic, the test is more likely to be valid. Testing hypotheses regarding effectiveness of a thing is consistent with validating *Theory for Prediction* (in which the effectiveness of the prediction is under test) or *Theory for Design and Action* (in which the effectiveness of the IT artifact is under evaluation) (Gregor 2006). Notably, although the development of a policy (as in Type I) may demand the evaluation of the policy (as in Type II), it does not imply they always co-occur in a single study, the point of which is roughly analogous to the relationship between theory development and theory test.

Note that, irrespective of specific adopted approaches, the validity of hypothesis testing heavily relies on the validity of the computational model used in representing real-world processes, events, and mechanisms. In other words, any hypothesis is indeed tested only when we accept that the computational model is at least to some extent true or useful in some respects.

The contribution type of Tester is intuitive and straightforward, often organized as: first clearly state the intended testable hypotheses and secondly describe the hypotheses testing results, highlighting the superior effectiveness of favored or advocated hypothetical arguments. Further, the hypotheses being tested may or may not be originally proposed in the study testing the hypotheses. Consider the following scripts, where hypotheses are not proposed in the study.

> Using an agent-based simulation and an empirical example based on actual television ad slot sales, we establish that **the rule-based combinatorial auction mechanism** proposed by Jones and Koehler [9] **can simultaneously serve all segments of the market**—as defined by varying constraints, budgets, and bidding strategies—in a single auction. The auction mechanism is not the focus of this paper [...] Nor is the focus on the design of the agent-based simulation—it is a means to an end, permitting us to explore **the premise that a single rule-based combinatorial auction can successfully sell to clients** with very different demand types, budgets, and bidding strategies while simultaneously solving a difficult capacity allocation problem. (Jones et al. 2006, p. 163, emphasis added)

In the following scripts, empirical data are used as simulation input to test the analytical results (i.e. the hypotheses in the study), making the hypothesis testing more convincing.

> We perform a simulation study **using publicly available traffic data regarding Amazon S3 clients from Alexa.com** to validate our analytical results. (Das et al. 2011, p. 756, emphasis added)

Though this type of contribution is ostensibly similar to and could be mixed with the previous type, the critical difference is, the development of a computational model and the conduct of computational experiments is mainly utilized to evaluate hypotheses; whereas, in the Analyzer type of contribution, the simulation model *per se* or the interpretation of simulation results for decision making, is often the main value. In other words, with the Tester type of contribution, the hypotheses and the testing of hypotheses can stand on their own without the computational model or simulation. For example, consider the following scripts, demonstrating the designed strategies in the study could be completely independent of the simulation model (i.e. if and when tested through other methods would have not changed the content of research findings); and the simulation modeling is merely utilized to evaluate the strategies.

> We **demonstrate the validity of designed strategies using a discrete event simulation model** that resembles the mechanisms used in treasury bills auctions, business-to-consumer (B2C) auctions, and auctions for environmental emission allowances. In addition, using the data generated by the simulation model, we **show that intelligent strategies can provide a high probability of winning an auction without significant loss in surplus**. (Adomavicius et al. 2009, p. 507, emphasis added)

Type III: Descriptor

The third type of contribution, Descriptor, is identified in 9 studies. To contribute to this type, the studies provide description of the phenomena of interest and explanations regarding the questions of, for example, what is, how, why, when, and where (Burton and Obel 1995; 2011; Axtell 2000; Carley 1996). It is often implicitly or explicitly argued that the computational modeling as well as the simulation result can uncover more formal and precise characterization of processes, mechanisms, and detailed contingent conditions that are otherwise not possible. Such description is useful to serve as a basic view or a fundamental understanding in all other kinds of investigation. Thus it has value to the IS theories of all types, including *Theory for Analysis, Theory for Explanation, Theory for Prediction, Theory for Explanation and Prediction*, and *Theory for Design and Action* (Gregor 2006).

This type of contribution is organized as: firstly present a summary of the situations or the phenomena of interest the study is intended to describe and then, often comparatively, highlight the strengths of the formal, more precise description and better understanding than previously related in the literature. The most common approaches to differentiate the new description from prior ones include, more realistically accounting for processes, mechanisms, and contingent conditions, as well as richer and more detailed characterization of interaction or dynamic mechanisms that are often difficult to concisely characterize through linear models or verbal illustration. Consider the following scripts.

> The contributions of this paper are twofold. First, this research presents a computational approach **integrating agent-centric and activity-centric concerns within process models**, which enables **the investigation of interactions** between agency, information, and decision structures. Second, **we focus on the interactions** between informational characteristics in process and incentive schemes in the context of a specific sales process model. (Raghu et al. 2004, p. 317, emphasis added)

> The theoretical development and the multi-agent model of this study contribute to the literature in several ways. First, to our knowledge, this study presents **the first formal characterization of the coordination problem during GSS transition**. (Nan and Johnston 2009, p. 270, emphasis added)

Further, the contribution type of Descriptor could combine with other contribution types in a single study. Consider the following example, where the study contributes to both Analyzer and Descriptor.

> This study makes several contributions to both research and practice. In terms of practice, the present study **provides managers with insight** into the effective planning, design, and reconfiguration of an IPN that will **help them, in the event of downsizing, to minimize impediments to information processing**. [...] This study provides researchers with **network-related conceptual underpinnings necessary for understanding various aspects of an IPN**, including its ontological structure, efficiency, and stability. (Kwon et al. 2007, p. 203-204, emphasis added)

When a study contributes to the Descriptor type, we argue it may have the potential to extend to other contribution types that are not readily and visibly constructed. The following example scripts only argued the contribution type of Descriptor. However, we sense more careful consideration and articulation of the practical usefulness of the simulation modeling work may yield the contribution type of Analyzer; for example, through consciously explicating and analyzing decision-making variables and contingencies of practical settings.

> Because of [...], we decided to **evaluate the benefits of four primary scenarios of CPFR to ascertain their effect** on collaborative and cross enterprise activities. In addition, because retailers have traditionally been playing the major role in supply chains in order to reduce bullwhip effects, we also investigated **the suitability of retailer- or buyer-driven collaboration and manufacturer- or supplier-driven collaboration in CPFR programs**. (Chen et al. 2007, p. 525, emphasis added)

> This paper makes several important contributions. It illustrates the need to consider the **interactions between an organization's business environment, threat environment, and characteristics (including sequence) of ISSCs** in order to evaluate ISSC portfolios. [...] This paper integrates the risk analysis, disaster recovery, and countermeasure portfolio perspectives and presents **a comprehensive set of parameters and model of their interactions**. [...] First, model variables and the simulation framework help researchers and managers better **understand and articulate key uncertainties and relationships** and pinpoint areas for information gathering. [...] Second, this paper contributes to **understanding interactions** between countermeasures [...] Third, experiment 3 contributes to an **improved understanding** of the dynamics of the interactions between countermeasures, threat, and business environments. [...] Finally, the model presented in this paper can be viewed as a systematic approach to assessing ISSC portfolio value. (Kumar et al. 2008, p. 270, emphasis added)

Type IV: Theorizer

The last type of contribution, Theorizer, is reported in 3 studies. In addition to providing description of the phenomena of interest, these studies also seek to explicitly formulate theoretical statements about the described phenomena. The statements could be (1) a set of theoretical hypotheses, (2) a set of theoretical assumptions, or (3) directions or exploration for future theory building (Burton and Obel 2011; Davis et al. 2007; Harrison et al. 2007).

Formulating theoretical hypotheses through simulation research are perhaps most apparently related to contributing to this type. It is also most extensively discussed in recent literature and generally considered to be one of the most important contributions from simulation research (Davis et al. 2007; Harrison et al. 2007). Further, formulating theoretical assumptions through simulation research is as equally important as explicitly formulating theoretical hypotheses from simulation research (Carley 2009), as challenging, extending, and/or modifying theoretical assumptions in fundamental ways remain to be most important efforts in making theoretical contributions (Whetten 1989). Additionally, explicating directions for future theory development is often regarded as an exploratory phase of theory building (Davis et al. 2007). Simulation methods for theory building might be most useful when investigating new phenomena (Davis et al. 2007). As such, exploring phenomena with simulation methods, analogous to exploratory case studies, may not eventually lead to testable theoretical hypotheses. Yet, such exploration may inform future theory development in significant ways, an excellent case being simulation modeling of organization disasters by Rudolph and Repenning (2002). Their creative analysis, although does not generate testable hypotheses or formulate theoretical assumptions, reveals how accumulation of minor interruptions can eventually lead to organizational crises, offering rich insights (e.g. the incorporating and distinction of two types of crises) for future theorizing the occurrence of organizational crises. To encourage such pilot effort with theory building, we emphasize the value from exploration with this contribution type. Further, consistent with the taxonomy of IS theory (Gregor 2006), the theory building effort may be of value for three IS theory types, *Theory for Explanation*, *Theory for Prediction*, and *Theory for Explanation and Prediction*.

This type of contribution is often organized as: first describe the phenomena of interest, and next formulate theoretical hypotheses or illustrate insights regarding theoretical assumptions and/or future theory building. The following scripts illustrate how investigation of the phenomena (i.e. observational learning) might inform future theoretical advancement (i.e. technology adoption).

> In the present research, we develop **a theoretical extension of the observational learning** model of Bikhchandani et al. (1992). [...] We use the model to develop new insights into situations in which **observational learning is a key component of technology adoption** decisions. (Walden and Rrowne 2009, p. 32, emphasis added)

The following scripts demonstrate an attempt to explicitly formulate theoretical hypotheses (i.e. “related to Orlikowski’s questions”) as well as inform future theory development (i.e. a framework for examining IT use).

> This study attempts to contribute to IS research by **proposing a framework specifically suited to the examination of bottomup IT use processes**. In particular, it seeks to extend the tenets and the instrument of complex adaptive systems (CAS) theory to the IS literature. [...] **Simulation results** from the various experimental treatments were **compared in answering Orlikowski’s questions**. First, [...] Second, [...] Third, [...] (Nan 2011, p. 506, emphasis added)

Theorizer, as one of the most important contribution types, can have impact on a broader research community. However, we identify few studies (i.e. 3) that explicitly construct this type of contribution. Again, we argue there is much further value possible from studies constructed other types of contribution, to extend their analysis to formulate contributions to Theorizer.

In example, the following script that constructed the contribution type Descriptor, might further yield value for Theorizer through illustrating how the theories of team cognition affecting IT impact, might be revised, extended, or tested.

> A first contribution of my paper is its **analysis of the impact of IT on the emergence of team cognition**. [...] By integrating the literature on the effects of IT on the emergence of team cognition, my study takes a step forward toward **the formalization of the IT implications in team dynamics and outcomes**. [...] The reflections on **the development of the other emergent states** as well as their interdependence are another contribution of this paper. (Curseu 2006, p. 258, emphasis added)

Studies that start from constructing a contribution to Theorizer may too have the potential to make other types of contribution such as Analyzer. The following scripts highlight a study with clear contribution to Theorizer. Although its potential to be applied in policy design is mentioned, the study may yield greater value if the exact practical settings, decisions or policies could be more readily available and explicit to potential consumers of the study.

> Simulation experiments show **how the dynamic behavior of offshoring is likely to evolve** beyond the current high-growth period. The model contributes to our understanding of offshoring by **offering a causal foundation for its growth pattern**. (Dutta and Roy 2005, p. 16, emphasis added)

> The contribution of our model lies in the development and testing of a computational representation of **the mechanics by which these factors interact to produce offshoring growth behavior**. Instead of examining inputs and outputs only, and viewing the offshoring process itself as a black box, we now have a computational view of what happens "inside the box." This can be **beneficial for policy making**, which, after all, involves systemic interventions intended to change system behavior in desirable ways. (Dutta and Roy 2005, p. 32, emphasis added)

Discussion

The aim of this paper has not been to critically assess previous simulation studies. Rather, we strongly empathize with such work and appreciate the value of simulation research. Thus this paper intends to firstly advocate for simulation studies to the general research community and secondly inform future simulation researchers to be more attuned to the value construction in simulation research. The implication of this research is substantial and multifold.

This research reaffirms the perceived low impact of simulation research in the IS field and offers an alternative explanation for this lack of influence. Although the citation analysis presented does not capture all aspects of research impact, we believe results reported in Tables 1 and 2 are sufficiently representative to suggest simulation methods are currently peripheral to mainstream methods being used by researchers to investigate IS phenomena. We encourage future researchers to replicate our research findings in other places. To maximize the impact, researchers not only need to continuously introduce and promote the rationale of simulation research, but also need to reconstruct contribution.

However, value construction in simulation research may need better attention. Though we have identified patterns of constructing contribution to the extent possible, we find it difficult to locate and clearly interpret the exact contributions of all sampled studies. This may be partially due to the complexities of any scientific research. But more importantly, it might be because contribution is not well constructed. For instance, in the sampled studies, contribution could appear in the beginning, the ending, the methodology, or the data analysis section. In some situations, contribution is mixed with the illustration of methodology adopted; that is, assuming value will surely follow if the methodology is appropriate. In other cases, contribution is mixed with description of simulation data analysis; that is, the presentation of data is assumed as value construction. This suggests, a shared common understanding regarding how best to construct contribution in simulation research, may not exist. It may further imply clear articulating and explicating contribution in simulation research is often not a focus of most studies. However, value construction might not be easy and intuitive as appears to be. As pointed out by several researchers (Davis et al. 2007; Locke and Golden-Biddle 1997; Weick 1989), a useful contribution needs to be well positioned and connected to the accepted knowledge in a field. Conducting the research but without consciously constructing the contribution is unlikely to result in high impact research. As such, in order to maximize their influence, researchers may need to be better attuned to the value construction.

Furthermore, we argue the typology of simulation contribution and its empirical instances may inform future simulation researchers to better think about and formulate contributions in their own research. Scientific research advances in accumulative manners. Knowingly or unknowingly, researchers draw from past scientific research practice to craft their own writings. The identified patterns of constructing research contribution in simulation research yield valuable insights; specifically, for future researchers to more efficiently access existing practices in the literature, to be more conscious about general types and patterns thereby using them as templates for creating their own masterpieces, and/or to build upon existing practices and to continuously reflex on and improve value construction in simulation research.

Lastly, it is also hoped the discussion in this paper will open a dialogue for researchers to debate on the value construction, for simulation research in particular and for all forms of scientific research in IS and will further stimulate ongoing thinking regarding the core issue of knowledge construction. The purpose of scientific research is said to create scientific knowledge. Yet, what constitutes a legitimate contribution to knowledge remains in flux and has been constantly debated such as in the field of management (e.g. Whetten 1989; Bacharach 1989). The IS field, commonly being perceived as a diverse discipline (Benbasat and Weber 1996), may more substantially benefit from such hard thinking on contribution to knowledge. Differing forms of scientific inquiries could have discriminative standards defining what is knowledge and how we can get it (Guba and Lincoln 1985). Thus, the IS field is in much need of such deep understanding of contribution to knowledge. Further, given historical concerns that the IS field is lacking its legitimacy (c.f. Benbasat and Zmud 2003; Baskerville and Myers 2002), a careful consideration of diverse forms of contribution to knowledge, may have the value to establish a solid foundation that justifies our research inquiries and helps us better understand the core disciplinary matters regarding how the field is likely to contribute most to the scientific enterprise.

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