Exploring Foundations for Using Simulations in IS Research

Completed Research Paper

Paolo Spagnoletti
Research Center on Information Systems (CeRSI), LUISS Guido Carli University, Roma, Italy
pspagnoletti@luiss.it

Stefano Za
Research Center on Information Systems (CeRSI), LUISS Guido Carli University, Roma, Italy
sza@luiss.it

Robert Winter
Institute of Information Management,
University of St. Gallen
St. Gallen, Switzerland
robert.winter@unisg.ch

Abstract

Simulation has been adopted in many disciplines as a means for understanding the behavior of a system by imitating it through an artificial object that exhibits a nearly identical behavior. Although simulation approaches have been widely adopted for theory building in disciplines such as engineering, computer science, management, and social sciences, their potential in the IS field is often overlooked. The aim of this paper is to understand how different simulation approaches are successfully used in IS research, thereby providing hypotheses that allow deriving methodological guidelines for subsequent studies. A survey of 69 pieces of IS research provides the grounding for defining a taxonomy of simulation approaches and for identifying possible application patterns linking simulation approaches to their theory contributions, research domains and information views.

Keywords: Simulation and modeling IS, Complex adaptive systems, System dynamics, Systems approach, Information views

Introduction

Simulation has been adopted in many disciplines as a means for understanding the behavior of a system by imitating it through an artificial object that exhibits a nearly identical behavior. This is especially true for physical systems whose behavior can be described by mathematical laws (e.g. differential equations) that allow to explain and to predict the phenomenon under investigation. In addition to such theory building capability, simulation approaches are also applied quite commonly in engineering design. In fact, though the behavior of separate components of a system can be well understood, validating the fit relationship between the assemblage and its environment is often problematic. Simulation can help in addressing this issue by providing a means for reproducing the system behavior in a controlled environment. Digital computers have greatly extended the range of systems whose behavior can be imitated through simulation techniques (Simon, 1996 p. 13). Systems that can be modeled and simulated span from natural to artificial ones and from biological to social systems.

Developing and validating theories through computational models of system behavior has been characterized as implementing the "what-might-be" research approach that – in addition to "what-is" and "what-should-be" – offers insights on the social behavior of humans (Burton and Obel 2011). Among the strengths of computational models there are the capability of ensuring high internal validity and the complementarities with other research methods (ibid). Simulation studies are considered particularly useful for building a place in which is easy to explore new concepts, ideas, boundaries and limitations but also for building predictive, and prescriptive theories (Casti 1997). In IS design science research, simulation is considered as one of the experimental design evaluation methods and is intended as "executing artifact with artificial data" (Hevner et al. 2004). Other IS studies use simulation for validating explanatory and predictive theories as suggested by reference disciplines such as operational research, management science, and artificial intelligence (Barbati et al. 2012; Davis et al. 2007; Kulik and Baker 2008; Lee and Kim 2008; Mielczarek and Uzialko-Mydlikowska 2010; Za and Spagnoletti 2013). Although the strengths of simulation are claimed to be promising in terms of theoretical rigor and scientific progress (Harrison et al. 2007), these studies still have a limited presence in theory development and validation – the IS research area that we want to address with this paper.

In their roadmap for simulation based theory building in management studies, Davis et al. (2007) define simulation as a method for using computer software to model the operation of "real-world" processes, systems, or events (Law and Kelton 1991). Simulations can be interpreted as virtual experiments (Carley 2001). According to Davis et al., "simulation involves creating a computational representation of the underlying theoretical logic that links constructs together, and these representations are coded into software that is run repeatedly under varying experimental conditions (e.g., alternative assumptions, varied construct values) in order to obtain results". As result of their research, they identify five simulation approaches: System Dynamics, NK fitness landscape, Genetic Algorithms, Cellular Automata and Stochastic Processes.

We use these five approaches as keywords, adding also the more general word "simulation", for performing our search on ISI Web of Knowledge, Scopus and AISeL. We search these keywords in both the "subject" and in the "abstract" on AISeL platform (http://aisel.aisnet.org/). Figure 1a summarizes the results. In order to evaluate the interest degree in the reference disciplines, we perform the same search on the Scopus platform (www.scopus.com). It is possible to refine the search results on the basis of several attributes, including the "Subject Area". We have used it to consider only the papers that belong to the main reference disciplines, considering those mentioned by Grover at al. (Grover et al. 2006): "Organization Science", "Management Science" and "Computer Science". Since on the Scopus platform there is not a total match between the possible "Subject Area" and the IS reference discipline, we consider the association shown in table 1. Also on Scopus we search the six keywords in the "keyword" and in the "abstract" attribute of the papers. The results are summarized in figure 1b.

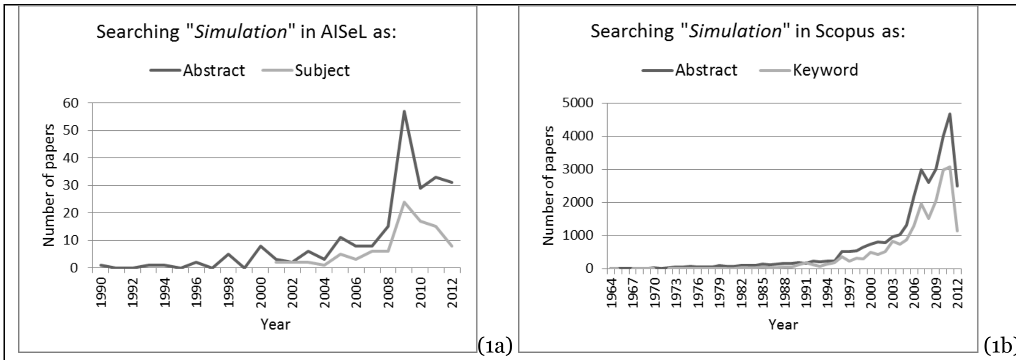

Figure 1. Simulation studies in IS field (1a) and in IS reference disciplines (1b)

Table 1. Main IS reference disciplines vs. subject areas on Scopus

Reference discipline	Subject Area on Scopus
Organization Science	Psychology Social Sciences
Management Science	Economics, Econometrics and Finance Business, Management and Accounting Decision Sciences
Computer Science	Computer Science

The number of publications per year in both data sets shows a growing interest for simulation studies. The decrease in the last two years in both data sets are likely due to meta data quality issues and should in our opinion not be interpreted as a sharply decreasing significance of simulation studies in IS. The positive trend of simulation studies is confirmed by considering selected papers as a percentage of the total amount of published papers. In particular, such studies in AISel are close to 0% before 2008 and between 1% and 2% after. Whereas, considering the papers belonging to the selected Subject Areas on Scopus, the percentage is less than 1% before 2006 and between 2% and 3% after. These evidences are coherent with the assumption that the increasing computational power and the growing amount of data available today, stimulate the development and continuous refinement of simulation methods, tools and techniques for research purposes.

The aim of this paper is to gain insights on the use of simulation in IS studies in order to understand how simulation is used in IS research in successful ways, thereby providing methodological guidelines for IS researchers in subsequent studies on that basis. For the purposes of this study simulation is understood as the use, for research purposes, of any artifact (i.e. model, method, instantiation) that imitates the behavior of the system under investigation. Therefore our objective is to answer the following questions: which simulation approaches have been used in the IS field? Is there any pattern or relationship between these approaches and the theory contribution, the research outcome and the authors' assumptions on the IS phenomenon under investigation?

Since simulation is a generic knowledge-creating strategy (i.e. reusable for many research questions) rather than a specific method (i.e. related to more or less specific questions and activities), it is hard to characterize potentials and limitations of simulation in IS in absence of a conceptual taxonomy. Such a taxonomy should comprise not only the input side (i.e., which specific type of simulation is applied), but also the output side (i.e., which specific type of results are created). To the best of our knowledge, a taxonomy which combines input and output side for simulation in IS does not exist.

This paper therefore aims at proposing such a taxonomy. Based on an analysis of publications in top-tier IS publication outlets, we explore whether certain types of simulation studies are related to certain types of theory contributions and / or to certain types of research domains. To this end, we first have to identify suitable classifications for simulation types, theory contribution types and research domain types. We ground our analysis on the work of Davis et al. (2007) on simulation based theory building methods in management studies, and on the five dimensions of analysis adopted by Lee (2010) in his retrospective and perspective analysis of IS studies.

In the next section we ground the dimensions of our analysis and we document the search and coding procedure for relevant simulation studies in IS publications. Afterwards we document the results of our analysis. Our findings and implications are discussed in the concluding section.

Methodological framework

As a general framework for grounding our analysis we refer to the five key concepts adopted by Allen Lee in his retrospective and prospective analysis of IS research, published in a special issue of the Journal of Information Technology (Lee 2010). Considered as foundational scientific constructs within the IS field, the concepts “information”, “system”, “theory”, “organization”, and “relevance” were used by Lee as dimensions for analyzing the past and providing directions for future IS research. Likewise, though addressing a narrower body of knowledge, we find these concepts useful for reflecting on the methodological assumptions of previous IS simulation studies and for opening a debate on the potential role of these studies along the IS research paths traced by Lee. Therefore we use them as lenses for understanding the theories-in-use by IS researchers when they apply simulation methods for developing theoretical knowledge.

Among the five concepts we selected the three that are more in line with our research goal. This leads us to discard the “system” and the “relevance” dimensions. Lee argues that the presence of systems concepts in much IS research “is, at best, only occasional and not plentiful” and often the label “information system” can be replaced by “information technology”. As a consequence, the systemic view that should characterize our field of studies is often neglected. In particular he points out that researchers need to undertake the major effort of accounting for the ties or interfaces between all parts of information systems. Therefore, by looking at the “system” concept as a potential dimension of analysis, would result in a dichotomy of studies in which variables are linked in a systemic way and studies in which they are not.

When we look at simulation methods adopted in management studies we can easily identify systemic constructs such as parts (i.e. agents, modules, etc.), ties (i.e. interactions, feedback loops, etc.), and levels (i.e. micro- macro-levels, etc.) that are used to model the phenomenon under investigation. Computational models are in fact defined as being “a specification of relations, equations, variables, parameters, rules, procedures, or more generally, algorithms that are computed” (Burton and Obel 2011). Since our dataset is built on a subset of such management studies, all the papers are expected to belong to the category of those showing a systemic view. Therefore the “system” dimension of analysis is discarded as a straightforward foundation of simulation approaches.

Furthermore, Lee defines “relevance” as "[a theory's] efficaciousness to managers and others in the 'real world' for the tasks that they need to accomplish". As we aim at exploring foundations for later proposing guidelines that help IS researchers to choose those (simulation) approaches that best match their respective research questions, our “managers and others in the ‘real world’” are researchers, their task is the creation of scientific IS knowledge, and efficaciousness means that applying our recommendations as a means needs to be effective in creating desired research outputs as an end. As a consequence, we do not need to differentiate different 'types' or 'classes' of simulation-based IS research with regard to relevancy, but can consider all observed simulation-based IS research as belonging to the same class of relevance, namely as scientific knowledge contributions in IS.

In the next subsections we define the three remaining key concepts of theory, organization, and information. For each of them we describe how it has been conceived by Lee, we motivate the relevance with respect to our research goal and we discuss how it has been conceptualized and translated into one of our dimensions of analysis.

Theory contribution

The first dimension of our analysis is related to the nature of the theory contribution of IS simulation studies. We are interested in exploring how simulation approaches have been successfully used for research purposes in the IS domain. Therefore it is relevant to understand if there are any relationships between simulation approaches and the nature of knowledge generated through simulation.

We follow the Lee's choice of adopting the classification of theory types proposed by Gregor (2006). Such taxonomy has been widely accepted in the IS community and classifies theories into five types: theory for analyzing, theory for explaining, theory for predicting, theory for explaining and predicting, and theory for design and action. Analytic theories focus on "what is" an IS phenomenon without explaining causality or attempting predictive generalizations. Classification schemas, frameworks, or taxonomies are typical contributions of such kind of theories. Davis et al. (2007) make an exemplary analytic theory contribution by proposing a classification of simulation approaches. The second type of theory explains primarily how and why phenomena occur. It often leads to a process-type theory and aims at better understanding the IS phenomenon instead of predicting it with any precision. As third type of theory, theories for predicting say what will be but not why. Therefore the interactions and connections among and systems parts and variables remain a "black box". In contrast, theories for explaining and predicting (fourth type) say what, how, why, when, and what will be an IS phenomenon. That implies both understanding of underlying causes and prediction, as well as description of theoretical constructs and the relationships among them. The fifth type, theories for design and action, gives explicit prescriptions for constructing an IT artifact intended as representational constructs, models, methods and instantiations (March and Smith 1995). These theories focus on principles of form and function, methods, and justificatory theoretical knowledge that are used in the development of IS (Gregor and Jones 2007).

Given the nature of simulation studies, which we defined as the use of any artifact that imitates the behavior of the system under investigation, we expect their theoretical contribution to be either explanatory and predictive or belonging to the design and action class of theories. In fact, it is unlikely that a simulation technique can be applied without having identified and modeled the parts of a system and their interconnections.

Research domain

The second dimension of our analysis is related to the organization concept. Lee (2010) argues that the scope of IS research should be the organizational and not just the technological aspects of an IS phenomenon. However, in IS studies the term "organization" has been monolithically referred to any and all people-related things. In fact, when focused on social phenomena, IS research is characterized by methodological individualism and therefore it fails in covering the non-individual phenomena that IS researchers encounter in the interactions between organizations and technology. His suggestion here is to change the focus of IS research by looking at an organization as a system in which both structural dimensions and individual level behavior contribute to determine the observed social regularities.

Such conceptualization leads us to investigate whether simulation studies are applicable to both organizational and technological aspects of IS phenomena and which are the methodological foundations of each approaches. We address these issues by analyzing the research domains of successful simulation studies and by looking for regularities in the association between simulation approaches and research domains.

In order to identify a useful research domain classification for our analysis we first refer to the common sense distinction between the technical and the social parts of an IS phenomenon. Therefore we distinguish those papers in which simulation is used to evaluate the performance of an IT artifact from those that are focused in understanding structural and agency aspects of social behavior. When social behavior is addressed, we borrow the Lee's definitions of methodological individualism and methodological holism for characterizing individual behavior and organizational behavior respectively.

This choice helps us in solving the issue of classifying research domains in IS in a way that is general enough but also specific with respect to our research purpose. In fact, although levels of analysis are widely recognized as a possible means for classifying IS phenomena, few approaches mix the artifact levels with the social levels. For instance, in their attempt to understand and optimize IS success/value, Kolfschoten and De Vreede (2009) overlook the IT artifact and only refer to the individual IT use, group IT use and process IT use. Another example is given by Mitra et al. (2011) who differentiate individual usage effects, business process effects and business unit effects for measuring IT performance and communicating value – but neglect the IT artifact role. In contrast to these approaches, our coding of the organizational dimension includes the IT artifact, the individual and the organizational behavior by borrowing concepts from more general taxonomies (Niederman et al. 2006).

Information view

Another important dimension to be considered in our analysis of simulation studies in the IS field is related to "information". In particular we investigate whether and how a given simulation approach implies some assumptions on the meaning of "information". Since the IS phenomenon refers to the behavior of an information processing system, the ways in which "information" is conceived by the researcher has many methodological and philosophical implications.

Also in this case we follow Lee by adopting the four views of information as defined by Mckinney and Yoos (2010) in their "Information about information" paper. This taxonomy distinguishes four views of information: the token, syntax, representational and adaptation view. In the token view information and data are both tokens manipulated by processes. In the syntax view information is the measureable relationship among tokens that reduces entropy. In the representation view information is meaning that emerges from a sign that stands for an object to a particular observer. Finally, in the adaptation view subjectivist assumptions are introduced to explain how information is created by a system. A shift toward an adaptation view of information has been advocated as a desirable direction for developing research in the IS field (Lee 2010).

It is worth to note that despite we borrow the definitions of the four views of information, the classification results obtained by coding simulation papers with these categories are different in general from those obtained by Mckinney and Yoos (2010) in building their taxonomy. In fact the two coding procedures have different purposes and therefore lead to different results. While McKinney and Yoos aimed at understanding how authors of selected papers have interpreted the information concept in the empirical IS phenomenon under investigation, we are interested in how information is conceived in the simulated system.

Search and coding procedure

As already mentioned in the introduction, we start building our taxonomy by assessing the applicability to our study of the five categories of simulation methods defined by Davis et al. (2007). According with such taxonomy, System Dynamics focus on the behavior of a system with complex causality and timing with a descriptive logic that explains how inputs to a system of interconnected causal loops, stocks, and flows produce system outcomes (Sterman 2001). NK fitness landscapes focus on the speed and effectiveness of adaptation of modular systems with an optimization logic that predict the optimal point of adaptation (Kauffman 1993). Genetic Algorithms focus on the adaptation of a population of agents with an optimization logic that predicts the optimal agent form through an evolutionary process (Holland 1998). Cellular automata focus on the emergence of macro patterns from micro interactions of agents with a descriptive logic (Wolfram 2002). Finally Stochastic Processes do not hold a specific theoretical logic and can be applied to a wide variety of research questions for complex systems with known probability distributions (Gallager 1996; Law and Kelton 1991). Although some categories of the taxonomy can be easily adopted in both cases, it is worth to note that the scope of our study is different from the previous one. While Davis et al. define simulation as "a method for using computer software to model the operation of real-world processes, systems, or events" we adopt a more general view on simulations by referring to any research approach that analyzes the behavior of a system imitating a real-world IS phenomenon. This means that the use of computers as a support tool for running the simulation is not mandatory in our case. This allows us to better explore the foundations of simulation studies in IS research.

Therefore as a first step of our survey, we select relevant literature from the IS basket journals (ISR, MISQ, JAIS, JMIS, JSIS, EJIS, JIT) using as topic keywords the five simulation types defined by Davis et al.

("system dynamics", "NK fitness landscape", "genetic algorithm", "cellular automata", and "stochastic processes") plus the more generic term “simulation”. The following query has been executed on the ISI Web of Knowledge database (http://apps.webofknowledge.com) where the asterisk-characters are used to include singulars and plurals.

```
Publication Name=("European Journal of Information Systems" OR "Information Systems Journal" OR "Information Systems Research" OR "Journal of the Association for Information Systems" OR "Journal of Information Technology" OR "Journal of Management Information Systems" OR "Journal of Strategic Information Systems" OR "MIS Quarterly") AND Topic=("system dynamic*" OR "NK fitness landscape" OR "genetic algorithm*" OR "cellular automat*" OR "stochastic process*" OR "simulation*")
```

The 88 papers returned by the query have been separately reviewed by two authors of the present paper in order to identify those that are relevant with the research question. Only papers that use simulation as a means for (any type of) theory building are taken into consideration. In this phase 19 papers have been considered as not relevant because they are focused on simulation as a topic instead of using it as a research method. For instance Leonardi (2011) provides a longitudinal study for explaining the effects on employees work practices of introducing a computer simulation technology for automotive design.

The resulting sample set of 69 papers (Appendix available at http://www.cersi.it/simulationICIS2013.pdf) has then been analyzed for defining a taxonomy of simulation approaches that is relevant to the IS domain. Afterwards each paper has been further coded into the categories identified for each dimension of analysis. The four dimensional space adopted for the analysis is illustrated by Figure 2. First, the theory contribution of the paper has been classified as being analytical, explanatory, predictive, explanatory and predictive, or aimed at design and action. Second, the research domain of each paper has been analyzed by distinguishing papers that focus on the IT artifact (i.e. construct, model, method, instantiation) and those that focus on a social phenomenon. The latter set has been further divided into papers that follows the methodological individualism assumption (individual behavior) and papers that refer to collective behavior (organizational behavior). Finally, the taxonomy of information views has been used as a further means for classifying the sample set of papers. The following questions have helped the researchers to implement this coding procedure: which view of information underpins the simulation model? Considering the token view and the adaptation views as a continuum, which assumptions are made by the researchers on the information exchanged among agents, subsystems, etc.? Is the meaning of information important in the model (token/syntax vs. representation/adaptation)? Is this meaning objective or subjective and strategically used by the agents (representation vs. adaptation)?

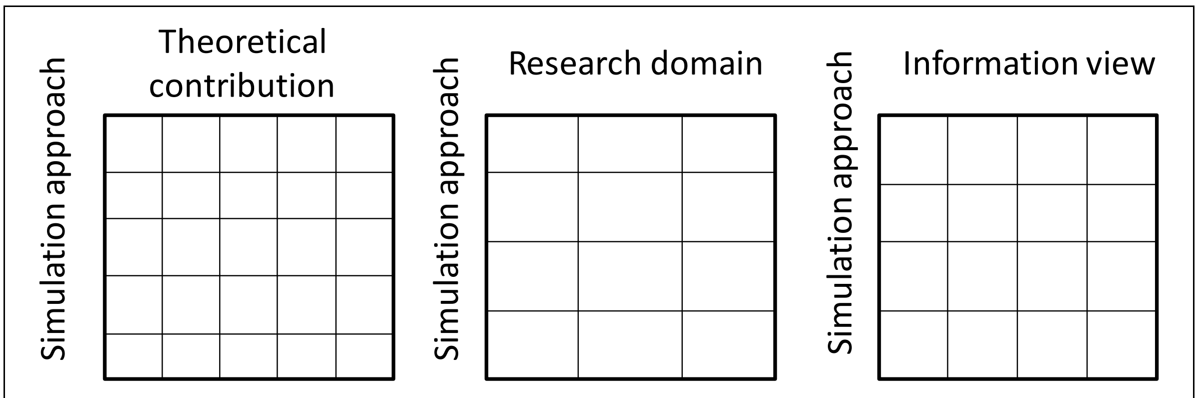

Figure 2. The four dimensional space of analysis

Results

Once the final sample of 69 papers published between 1988 and 2012 has been identified, these papers have been separately read and classified into one of the taxonomical categories defined by Davis et al.

(2007). As a result of such first iteration, the three categories “NK fitness landscape”, “genetic algorithm” and “cellular automata” have been merged into one category named “agent based” (AG) simulation approach. This allows to both group a sufficient number of papers (17 papers) that can be further analyzed along the proposed dimensions (theory, research domain, information) and to take into consideration agent based models that do not fit with any of the three predefined classes of algorithms. In general an agent based model is described through a set of parameters that characterize the environment in which the agents act, and a set of more or less complex functionalities (behavior) and attributes (the internal states) of an agent (Nan 2011). The agent state can be also based on its cognitive perception (real or believed) of the reality (i.e. beliefs, trust, dependence). Cellular automata, genetic algorithms and the NK fitness landscape also belong to this category (e.g. Dawande et al. 2008). The AG simulation approaches share the common assumption that the IS phenomenon emerges from the interaction among agents / modules and cannot be predicted from the characteristics of the single agents or from the rules of their interaction (Curşeu 2006). Nine papers out of twelve have been published in ISR, the others in JIT, MISQ, and ISJ.

Four papers published in four different journals (EJIS, MISQ, JSIS, ISR) and three papers published in JMIS fall into the “system dynamics” (SD) category. IS studies in this subset explicitly refer to the view of a system as composed by processes that have some common constructs and hence interact in a set of circular causal loops (Sterman 2001). These causal loops can be positive or negative depending on the characteristics of the feedbacks.

Our third category corresponds to the “stochastic processes” (ST) as defined by Davis et al. (2007). Twelve papers fall in this category and the majority of them are published in MISQ or in ISR with few exceptions (one paper was published in EJIS and two in JMIS). These studies are characterized by the use of statistical simulations (e.g. Monte Carlo simulation, correlation coefficient analysis, etc.) and are also based on existing building blocks for processes (i.e. Markov chains) and stochastic sources (i.e. Poisson distribution). Often this kind of simulations are used as a way for producing huge dataset on which to perform the test of some kind of regression model (e.g. PLS) (Goodhue et al. 2007; Zheng and Pavlou 2009).

Two additional categories have been defined in addition to those identified by Davis et al.: “analytical” (AN) and “human based” (HU) simulations. Analytical simulations concern the use of a mathematical model for simulating some specific phenomena. For instance, Koushik and Mookerjee (1995) provide an analytical model for supporting a macro-level decisions regarding the development team size and the coordination policy, based on micro-level interactions between the modules in a system. The focus is on the use of a formal model (the algorithm designed ad hoc) rather than a statistical simulation for testing and validating it. Twenty-two papers fall under this category; nearly all are published in ISR (eleven papers) and JMIS (seven papers) with the exception of two papers in MISQ, one in JAIS and one in EJIS.

The last category that we define is that of “human based” (HU) simulations. Simulations in this category can be considered as AG simulations in which the agents are humans (Wastell 1996). In these studies groups of people are involved in a game in which they interact in a simulated world (e.g. business game). The use of this simulation is performed when the behavior of an agent becomes too complex for being embedded into the cognitive model of an artificial agent (Rafaeli and Noy 2002). In this kind of simulations the use of artificial agents can also be adopted for populating the environment in which the individuals act (Kanawattanachai and Yoo 2002). Furthermore, in some of these papers HU simulation is used as an evaluation method in the design of an IT artifact. The eleven papers that fall in this category have been published in seven different IS basket journals.

In the following subsections we report the findings of our interpretation of the classification results along the three dimensions identified.

Simulation type vs. theory contribution

By looking at the distribution of simulation approaches along theory contribution types, we evidence that simulation types AG, AN, HU and SD contribute to explanatory / predictive theory building as well as to design theory building. On the contrary ST clearly only contributes to design theory building.

Table 2. Simulation type vs. theory contribution

Theory / Simulation	analysis	explanation	prediction	explanation and prediction	design and action
AG	1	6		3	7
AN	1	1		13	7
HU				6	5
SD				5	2
ST		2			10

Our interpretation of this result is that ST simulations can rarely support explanation because simulation requires existing explanatory knowledge in order to be run. Nevertheless, some limited amount of explanation becomes possible when patterns of behavior are identified in stochastically generated data. For instance Oh and Lucas (2006) found that in online computer markets small price increases occur more frequently than decreases, while the frequency of price adjustment is significantly associated with a product's price dispersion.

Ten out of twelve papers in the ST category refer to the design and improvement of some data analysis technique (Chin et al. 2003, 2012; Goodhue et al. 2007, 2012) through statistical simulations such as Monte Carlo (Qureshi and Compeau 2009). Data analysis techniques, the objects of study of these papers, can be applied to many research domains with different information views. This motivates us to discard the ST category from the following steps of our qualitative analysis.

Our results confirm the twofold value of simulation as proposed by Simon. Simulation studies allow to analyze the behavior of an imitated system and to add explanatory and predictive knowledge on the behavior of the real-world system. Furthermore, being grounded in the engineering tradition, all categories of simulation studies play an important role as a powerful tool for the definition of what-might-be scenarios and hence as an evaluation technique in design and action research.

Finally it is worth to note that AG simulation, although being used for explanation as well as explanation and prediction, seems to have a special focus on explanation rather than prediction. A possible interpretation of this finding is that, as opposed to other simulation approaches, some AG models can be grounded on different epistemological assumptions. This is, e. g., the case for models grounded on complex adaptive systems (CAS) theory (Curşeu 2006; Nan 2011). In such models the focus is on the emergence of patterns of agents interactions that provides insights for understanding some collective behaviors (Raghu et al. 2004; Rao et al. 1995) instead of the defining some deterministic predictive rule. Another reason for the explanatory nature of agent-based simulation uses is the validation issue. In order to use AG for prediction, the model has to be validated further. The amount of effort required by such validation is often prohibitive. Therefore, most AG studies chose to stay on the explanatory level.

Simulation type vs. research domain

As already mentioned in the previous section, ST simulation studies have been excluded from this analysis since stochastic approaches are too generic to be specifically related to a specific IS research domain. The results of the classification of IS simulation approaches into the categories of the research domain taxonomy show that AG simulations are clearly related to individual behavior and that AN as well as SD are less related to individual behavior. HU and AG focus on behavior rather than on artifact. For instance the paper by (Dawande et al. 2008) applies an agent based model for simulating the dynamics of pair development in software projects and to compare performances with solo and mixed development. In contrast, AN studies are mostly focused on the IT artifact such as the case of the Mookerjee et al. (1995) paper on improving the performance stability of inductive expert systems under input noise or the Datta et al. (2012) on SOA performance enhancement through XML fragment caching. Finally the Wong et al. (2012) paper that applies the artificial immune systems principles to credit card fraud detection provides an example of how an AG simulation approaches can be adopted for assessing the validity of an IT artifact.

Table 3. Simulation types vs. research domain

Research domain / Simulation	Individual behavior	Organizational behavior	IT artifact
AG	10	4	3
AN	4	7	11
HU	6	3	2
SD	1	3	3

These evidences are also coherent with the Lee's argument that IS studies are characterized by methodological individualism – but the four categories of studies considered so far also address the organizational behavior research domain. Therefore a further look into these papers can provide examples on how to address the methodological individualism vs. methodological holism debate.

Although a detailed analysis of the research purposes of these papers is beyond of the scope of this paper, it is worth to note that 10% of our dataset is related to modeling the human behavior in online auction settings. A deep investigation on how this phenomenon has been studied might bring further insights on the use of simulation in IS research.

Simulation type vs. information views

Table 4. Simulation types vs. information views

Information views / Simulation	token	syntax	representational	adaptation
AG			11	6
AN		22		
HU				11
SD			7	

The results of the analysis along the information view dimension show that none of the simulation studies from our sample adopt a token view of information. According with Mckinney and Yoos (2010), in the token view information is synonymous with data manipulated by processes without any particular relations among the bits (syntax), nor how a bit represents an object to an observer (representation), nor how a bit alters the system. This can be explained as it is unlikely that in a simulation study, in which the behavior of an IS phenomenon is imitated through an artificial system, data are just processed without any relations that can either be an analytical function (i.e. AN), an information flow (SD), an information exchange (AG), or a knowledge interpretation (HU). Therefore, simulation seem to be a good candidate for enlarging the scope of IS studies as suggested by Lee. Furthermore, an information system can be seen as being in a continuous state of emergence from the interactions among its three constituent subsystems: the technology system, the organization system, and the data system. In such view of IS phenomena, the interactions continuously transform the data into what the syntax, representation, or adaptation views would consider to be information (Lee 2010).

The analysis also shows that AN simulations adopt a syntax view of information. This is the case for instance of the mechanism for SLA formulation for IT infrastructure services proposed by Sen et al. (2009) in which data such as demand fluctuations and user preferences are linked to maximize organizational welfare of the participants.

SD simulations adopt a representational view of information. System dynamics models are in fact based on the representation of flows, stocks and feedback loops in which information are universally and objectively defined as having the same meaning for any observer. This is the case, e. g., for the planning model for network services proposed by Dutta (2001) that links in a circular way business performance, the size of a provider's customer base, price and network performance.

HU simulations adopt an adaptation view of information. This finding does not need any further explanation since human based simulation approaches are used when the complexity of human decision making is taken into account together with the rules of the game that reproduce the system. For instance Wastell (1996) uses a rich simulation (a 'microworld') for gaining insights on the human-machine dynamics in digitally supported work environments.

AG simulation is the only approach that exposes a twofold character with respect to the information view dimension. It can either adopt representational view or an adaptation view depending on how the cognitive model of the agent's minds is conceived. When adopting a representation view, AG models assume that agents strategically act in their environment by processing some objective and universal information. This is the case for instance of bidders behavior in online auctions as modeled by Bapna et al. (2003). On the contrary, when agents also behave according with their subjective perception of some real-world representation, AG models fall into the adaptation view of information and promise to solve many limitations of HU for understanding complex phenomena. This is the case for instance of the representation of team cognition, trust, cohesion and conflict which are described as emerging states in interacting agents whose collective behavior impacts on the virtual team effectiveness and at the same time is influenced by the outcomes of a virtual team (Curşeu 2006).

Discussion and implications

With this paper, we aimed at exploring how simulation approaches are used in IS research in order to create foundations for elaborating guidance on which simulation approaches are most suitable for particular theory contributions, particular research domains or particular information views. For that purpose, we identified 69 publications in top-tier IS journals that use simulation methods. In order to identify application patterns, we used established taxonomies for simulation approach, theory contribution, research domain and information view to code the primary positioning of each publication regarding our research questions. Based on two independent codings, we summarize our findings as follows:

- Regarding theory contribution, only stochastic simulation approaches are limited to theories for design and action. All other simulation approaches have been successfully used for all types of theory contribution, with agent-based simulation approaches being mostly used in the context of explanatory theory.
- While agent- and human-based simulation mostly are applied for explaining individual or organizational behavior, system dynamics and analytical simulation are usually applied to analyze or design IT artifacts. Among those simulation approaches that are used in behavior studies, agent-based simulation approaches are the only type that is clearly focused on individual behavior.
- The strongest dependencies were observed when relating simulation types to the dominant information view in the respective research. Analytical, system dynamics and human-based simulation is clearly assuming the syntax, representation, and adaptation view of information, respectively. Agent-based simulation is mostly assuming the representation view, while few studies assume the adaptation view of information.

Since we are focusing on IS research in this study, a limitation of our findings is that more 'technical' IS research papers (e. g., those published in ACM transactions or IEEE transactions) are not covered by our analysis. The same limitation holds for recent studies and for results that have been published in other IS research outlets (including conference proceedings) than the ones we analyzed. Like in any explorative study, analysis results might be different if additional observations are included or current observations are excluded. We are however confident that the current selection of outlets is sufficiently representative to explore useful hypotheses for further research.

Since the strongest relationship was observed between simulation approaches and information view, we now elaborate on this discovery. Allen and Varga (2006) argue that the analysis of IS can be characterized by successive simplifications that lead to an increasing reduction of emergence and individual perceptions of IS. By transforming the representation of reality into evolutionary models, then self-organizing models, then deterministic systems and finally into equilibrium models, complexity is stepwise reduced, but constraints (like classification, averages, equilibrium) are successively added. Since Mckinney and Yoos (2010) understand their proposed taxonomy of information views in pieces of IS research as a layered system rather than a system of independent classes, we can interpret simulation types in the context of IS research as a layered system.

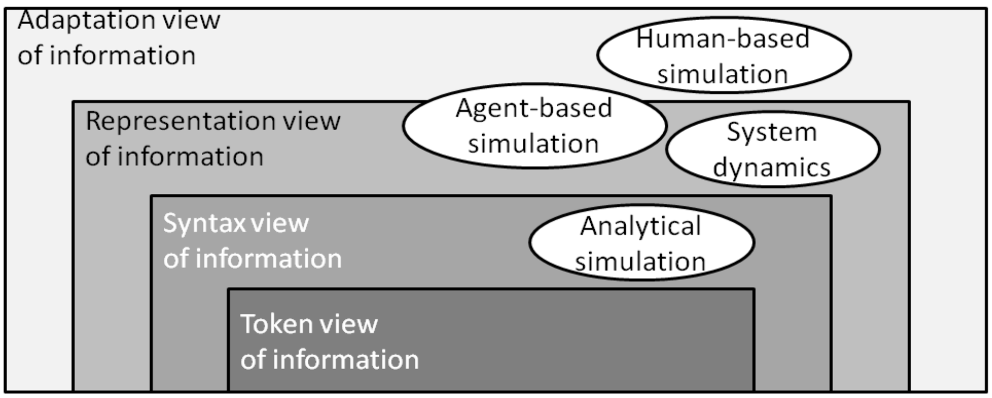

Figure 3. Simulation approaches correspond to information view layers

Figure 3 illustrates the resulting, layered taxonomy of simulation approaches based on the information view according to Mckinney and Yoos (2010). It can be interpreted as follows: All simulation goes beyond the token view of information because at least information syntax must be sufficiently understood in order to apply simulation. While analytical simulations realize only this level of information understanding, other simulation approaches go one or two steps further. System dynamics and most agent-based simulations realize the representation view of information, while some agent-based simulations and all human-based simulations are positioned on the top layer, i.e. realize the adaptation view of information. If information views can be interpreted as a layered system of increasing levels of understanding and expressive power, respective simulation approaches also can.

This insight could be useful as a methodological guideline in the context of IS, the domain where our research is intended to provide foundational knowledge for. If the intended and feasible information view is clarified for a research project, the choice of applicable simulation approaches is limited to one, maybe two classes out of the five existing classes. It can be expected that a detailed analysis of the respective information view – simulation type paper sets will provide more detailed insights which sub-types of simulations are most likely to be successfully applicable for which type of research questions. If sufficiently strong and detailed results are achieved, the exploratory analysis might then be transformed into methodological recommendations: for a sub-class of research questions in a certain information view layer, specific simulation approaches are then recommended that promise to be best applicable in that situation.

By translating the use of simulation by existing high-quality research papers into methodological guidelines in such a straightforward way, we are aware that there might be potential applications for simulation that have not been explored yet sufficiently – e.g. 'overlooked' as we have formulated it in the introduction. There might always exist new and promising ways to approach a research question beyond what is suggested by guidelines that rely on empirical evidence. Patterns help to find a promising start and to avoid clear dead ends. Patterns should however not be misused to replace methodological creativity, in particular in a research field whose (compared to reference disciplines) lower maturity always suggests to be open for approaches that go beyond established patterns.

Acknowledgments

We thank the Track Chairs and the review team for their encouraging comments and suggestions. Their guidance has helped us in revising the paper by strengthening the validity of our findings and pointing out some additional insights in the discussion of results.

References

Allen, P. M., and Varga, L. 2006. "A co-evolutionary complex systems perspective on information systems," *Journal of Information Technology* (21:4), pp. 229–238.

Bapna, R., Goes, P., and Gupta, A. 2003. "Replicating online Yankee auctions to analyze auctioneers' and bidders' strategies," *Information Systems Research* (14:3), pp. 244–268.

Barbati, M., Bruno, G., and Genovese, a. 2012. "Applications of agent-based models for optimization problems: A literature review," *Expert Systems with Applications* (39:5)Elsevier Ltd, pp. 6020–6028.

Burton, R., and Obel, B. 2011. "Computational modeling for what-is, what-might-be, and what-should-be studies—And triangulation," *Organization Science* (22:5), pp. 1195–1202.

Carley, K. M. 2001. "Computational approaches to sociological theorizing," in *Handbook of sociological theory*, J. Turner (ed.), New York: Kluwer Academic/Plenum, pp. 69–84.

Casti, J. L. 1997. *Would-Be Worlds: How Simulation is Changing the Frontiers of Science*, New York, NY: John Wiley and Sons.

Chin, W. W., Marcolin, B. L., and Newsted, P. R. 2003. "A Partial Least Squares Latent Variable Modeling Approach for Measuring Interaction Effects: Results from a Monte Carlo Simulation Study and an Electronic-Mail Emotion / Adoption Study," *Information Systems Research* (14:2), pp. 189–217.

Chin, W. W., Thatcher, J. B., and Wright, R. T. 2012. "Assessing common method bias: Problems with the ULMC technique," *MIS Quarterly* (36:3), pp. 1003–1019.

Curşeu, P. L. 2006. "Emergent states in virtual teams: a complex adaptive systems perspective," *Journal of Information Technology* (21:4), pp. 249–261.

Datta, A., Dutta, K., Liang, Q., and VanderMeer, D. 2012. "SOA Performance Enhancement Through XML Fragment Caching," *Information Systems Research* (23:2), pp. 505–535.

Davis, J. P., Eisenhardt, K. M., and Bingham, C. B. 2007. "Developing Theory Through Simulation Methods," *Academy of Management Review* (32:2), pp. 480–499.

Dawande, M., Johar, M., Kumar, S., and Mookerjee, V. S. 2008. "A Comparison of Pair Versus Solo Programming Under Different Objectives: An Analytical Approach," *Information Systems Research* (19:1), pp. 71–92.

Dutta, A. 2001. "Business planning for network services: A systems thinking approach," *Information Systems Research* (12:3), pp. 260–283.

Gallager, R. 1996. *Discrete stochastic processes*, Boston: Kluwer Academic Publishers.

Goodhue, D., Lewis, W., and Thompson, R. 2007. "Statistical Power in Analyzing Interaction Effects: Questioning the Advantage of PLS with Product Indicators," *Information Systems Research* (18:2), pp. 211–227.

Goodhue, D., Lewis, W., and Thompson, R. 2012. "Does PLS Have Advantages for Small Sample Size or Non-Normal Data?," *MIS Quarterly* (36:3), pp. 981–1001.

Gregor, S. 2006. "The nature of theory in information systems," *MIS Quarterly* (30:3), pp. 611–642.

Gregor, S., and Jones, D. 2007. "The anatomy of a design theory," *Journal of the Association for Information Systems* (8:5), pp. 312–335.

Grover, V., Ayyagari, R., Gokhale, R., and Lim, J. 2006. "A Citation Analysis of the Evolution and State of Information Systems within a Constellation of Reference Disciplines," *Journal of the Association for Information Systems* (7:5), pp. 270–325.
Harrison, J., Zhiang, R., Carrol, G., and Carley, K. M. 2007. "Simulation modeling in organizational and management research," *Academy of Management Review* (32:4), pp. 1129–1245.
Hevner, A. R., March, S. T., Park, J., and Ram, S. 2004. "Design science in information systems research," *MIS Quarterly* (28:1), pp. 75–105.
Holland, J. 1998. *Emergence: From chaos to order*, *Complexity*, New York: Basic Books, p. 258.
Kanawattanachai, P., and Yoo, Y. 2002. "Dynamic nature of trust in virtual teams," *The Journal of Strategic Information Systems* (11:3-4), pp. 187–213.
Kauffman, S. 1993. *The origins of order*, New York: Oxford University Press.
Kolfschoten, G. L., and de Vreede, G.-J. 2009. "A Design Approach for Collaboration Processes: A Multimethod Design Science Study in Collaboration Engineering," *Journal of Management Information Systems* (26:1), pp. 225–256.
Koushik, M., and Mookerjee, V. S. 1995. "Modeling Coordination in Software Construction: An Analytical Approach," *Information Systems Research* (6:3), pp. 220–254.
Kulik, B. W., and Baker, T. 2008. "Putting the organization back into computational organization theory: a complex Perrowian model of organizational action," *Computational and Mathematical Organization Theory* (14:2), pp. 84–119.
Law, A. M., and Kelton, D. W. 1991. *Simulation modeling and analysis*, (2nd ed.) New York: McGraw-Hill.
Lee, A. S. 2010. "Retrospect and prospect: information systems research in the last and next 25 years," *Journal of Information Technology* (25), pp. 336–348.
Lee, J. H., and Kim, C. O. 2008. "Multi-agent systems applications in manufacturing systems and supply chain management: a review paper," *International Journal of Production Research* (46:1), pp. 233–265.
Leonardi, P. 2011. "When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies," *MIS Quarterly* (35:1), pp. 147–167.
March, S. T., and Smith, G. F. 1995. "Design and natural science research on information technology," *Decision Support Systems* (15:4), pp. 251–266.
Mckinney, E. J., and Yoos, C. I. 2010. "Information about information: A taxonomy of views," *MIS Quarterly* (34:2), pp. 329–344.
Mielczarek, B., and Uzialko-Mydlikowska, J. 2010. "Application of computer simulation modeling in the health care sector: a survey," *Simulation* (88:2), pp. 197–216.
Mitra, S., Sambamurthy, V., and Westerman, G. 2011. "Measuring IT performance and communicating value," *MIS Quarterly Executive* (10:1), pp. 47–59.
Mookerjee, V. S., Mannino, M. V., and Gilson, R. 1995. "Improving the performance stability of inductive expert systems under input noise," *Information Systems Research* (6:4), pp. 328–356.
Nan, N. 2011. "Capturing bottom-up information technology use processes: a complex adaptive systems model," *MIS Quarterly* (35:2), pp. 505–532.
Niederman, F., Davis, A., Greiner, M., Wynn, D., and York, P. 2006. "A Research Agenda for Studying Open Source I: A Multi-Level Framework," *Communications of the AIS* (18), pp. 129–149.
Oh, W., and Lucas, H. 2006. "Information technology and pricing decisions: Price adjustments in online computer markets," *MIS Quarterly* (30:3), pp. 755–775.
Qureshi, I., and Compeau, D. 2009. "Assessing between-group differences in information systems research: a comparison of covariance-and component-based SEM," *MIS Quarterly* (33:1), pp. 197–214.
Rafaeli, S., and Noy, a. 2002. "Online auctions, messaging, communication and social facilitation: a simulation and experimental evidence," *European Journal of Information Systems* (11:3), pp. 196–207.
Raghu, T. S., Jayaraman, B., and Rao, H. R. 2004. "Toward an Integration of Agent- and Activity-Centric Approaches in Organizational Process Modeling: Incorporating Incentive Mechanisms," *Information Systems Research* (15:4), pp. 316–335.
Rao, H., Chaudhury, A., and Chakka, M. 1995. "Modeling team processes: Issues and a specific example," *Information Systems Research* (3:6), pp. 255–285.

Sen, S., Raghu, T. S., and Vinze, A. 2009. "Demand Heterogeneity in IT Infrastructure Services: Modeling and Evaluation of a Dynamic Approach to Defining Service Levels," *Information Systems Research* (20:2), pp. 258–276.

Simon, H. 1996. *The Sciences of the Artificial*, (3rd ed., Vol. 4) MIT Press, p. 215.

Sterman, J. D. 2001. "System Dynamics Modeling: Tools for Learning in a Complex World," *California Management Review* (43:4), pp. 8–25.

Wastell, D. 1996. "Human-machine dynamics in complex information systems: the 'microworld' paradigm," *Information Systems Journal* (6), pp. 245–260.

Wolfram, S. 2002. *A new kind of science*, Champaign, IL: Wolfram Media.

Wong, N., Ray, P., Stephens, G., and Lewis, L. 2012. "Artificial immune systems for the detection of credit card fraud: an architecture, prototype and preliminary results," *Information Systems Journal* (22:1), pp. 53–76.

Za, S., and Spagnoletti, P. 2013. "Knowledge creation processes in Information Systems and Management: lessons from simulation studies," in *Organization Change and Information Systems, LNISO vol. 2*, P. Spagnoletti (ed.), Heidelberg: Springer.

Zheng, Z., and Pavlou, P. a. 2009. "Toward a Causal Interpretation from Observational Data: A New Bayesian Networks Method for Structural Models with Latent Variables," *Information Systems Research* (21:2), pp. 365–391.