Microeconomically founded Information Systems Research

Jan Krämer*   Daniel Schnurr†

January 15, 2016

Abstract

We advocate to develop IS theories on the basis of formal, analytic models, which in turn facilitate the deduction of design and engineering proposals as well as testable hypotheses. However, we also believe that these formal models and theories should be both, well grounded in stylized empirical facts that are the result of inductive research efforts, as well as evaluated and refined through empirical analyses based on field studies and laboratory experiments. To this end, we motivate and discuss a microeconomically founded IS research process cycle that we deem suitable to develop IS theories that are rigor and relevant.

Keywords: Philosophy of Science; Information Systems Research; Economics of IS; Theory; Model

*Chair of Internet and Telecommunications Business, University of Passau, Dr.-Hans-Kapfinger-Str. 12, 94032 Passau, Germany. Tel: +49 851 509 2580, fax: +49 851 509 2582, e-mail: jan.kraemer@uni-passau.de.

†Chair of Internet and Telecommunications Business, University of Passau, e-mail: daniel.schnurr@uni-passau.de.

1 Introduction

It is our fundamental understanding that the main purpose of IS research, like most other research disciplines, should be the development of robust theories, which can then inform us about the likely answers to our research questions. What is notable, although not unique, about IS research is that the research questions that we pursue are not only concerned with the *understanding*, *explanation* and possibly *prediction* of real world phenomena, but also with how we can shape the institutions (North, 1991; Roth, 2002) that govern these phenomena in order to achieve a certain goal (cf. Gregor, 2006). In this regard, IS research takes a theory-guided *engineering* perspective.

Consider the domain of electronic markets, for example. IS research may be interested in *why* an observed (e.g., technology induced) market behavior occurs, *which* market outcomes are likely under a given scenario, but also *how* markets should be designed in order to achieve a desirable outcome.

In the following we will develop and discuss what we call an idealized microeconomically founded IS research process cycle, depicted in Figure 1, which reflects our view that fruitful IS theories can be built upon formal, analytic models. Such models are in turn founded upon both, stylized facts that are derived from empirical regularities observed in reality, as well as the existing body of knowledge stemming from robust theories. With reality, we denote the object and processes of investigation that research intents to describe or understand. Scientific inquiries are either concerned with realizations of the *past* or with potential *future* states. Researchers perceive reality through empirical observation and data gathering, which is naturally constrained and imperfect. Models, which in themselves are the foundation of theory, can then be used to explain, predict and design instances of the real world. Finally, models, and thus also theory, are evaluated and refined with respect to their ability to inform us about past or future real world phenomena. This can be achieved in field or laboratory studies either by validating or falsifying theory-guided hypotheses, comparing a theory's predictions with actual future outcomes or by evaluating the success of theory-informed design proposals and engineering approaches in actual applications.

The herein described research paradigm is more specific than (but not contradictory to) more general IS research paradigms (cf. Frank, 2006), such as design science (cf., e.g., Hevner et al., 2004). Nevertheless, we will argue that theories developed under this framework are suitable to pursue all four fundamental goals of IS research, namely analysis, explanation, prediction, and prescription/design (cf. Gregor, 2006). It is not our intention, however, to evaluate or judge different IS research approaches, but rather to motivate why we believe that the proposed microeconomically founded research paradigm is one of several appropriate means to rigorously develop relevant IS theories.

2 The building blocks of microeconomically founded theory development

Theory as a set of models In general, theory has been characterized as the "basic aim of science"(Kerlinger, 1986, p.8) and is often referred to as "the answer to queries of why" (Kaplan and Merton cited by Sutton and Staw, 1995, p.378). According to Weick (2005, p.396) a theory may be measured in its success to "explain, predict, and delight".

In explaining our precise understanding of "theory", we start from the premise that the

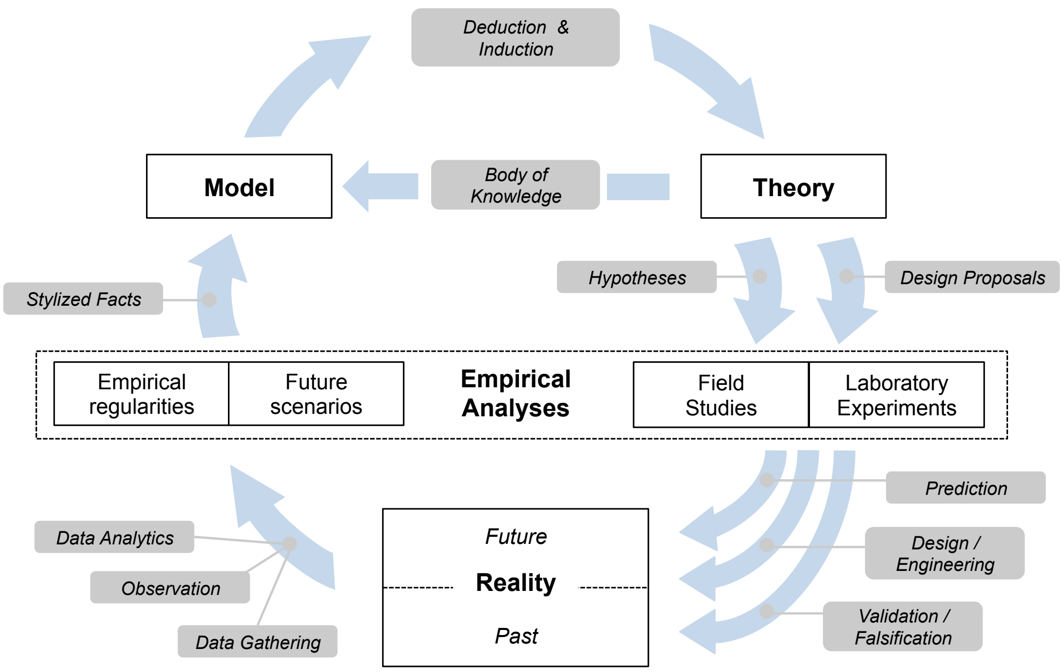

Figure 1: Idealized microeconomically founded IS research process cycle.

main task of theory is the integration of findings of individual studies into a modular, but coherent *body of knowledge* that connects research agendas based on a shared terminology and which provides a *microfoundation*. Revision and extension of theory is achieved in iterative steps through new or modified models that may either re-investigate central assumptions, thus deepening theory's microfoundation, or create meta-models by further abstraction based on the existing body of knowledge. By this means, a *mircofounded* theory serves as an anchor (Dasgupta, 2002) and provides building blocks for new research projects and further theory-building.

In our view, robust theories are the result of deduction and induction from a host of formal models. Therefore, theory can be viewed as a classified set or series of models (Morgan and Knuuttila, 2012). In philosophy of science this integral role of models as a part of the structure of theory has been supported by the Semantic View and has been further emphasized by the Pragmatic View (Winther, 2015). Consequently, a clear distinction between theory and its models is difficult in general, and even more so if the analysis of theoretical models is deemed as the central part of scientific activity.

At the extreme, a single model can already be the foundation of a theory, although probably not a very robust one. In this regard, the understanding of a robust theory in the social sciences may differ from the understanding of a robust theory in the natural sciences, because theory in the social sciences can be very context dependent, as subjectivity of decision makers, i.e., their beliefs, information, and view of the world substantially shape their choices and actions (Hausman, 2013). For example, Dasgupta (2002, p.63) noted that "the physicist, Steven Weinberg, once remarked that when you have 'seen' one electron, you have seen them all. [...] When you have observed one transaction, you have not observed them all. More tellingly, when you have met one human being, you have by no means met them all". This is why a robust theory in the social sciences should regularly be built upon a set of models, each of which takes a different perspective on a particular issue and explores a slightly different set of assumptions, such that the boundaries of the theory become transparent.

Models as the mediator between theory and reality This understanding of theory shifts our attention to the development of suitable models. Models as *idealizations* (Morgan and Knuuttila, 2012) serve as representations of reality that are obtained by simplification, abstraction (see, e.g., the work of Cartwright, 2005; Hausman, 1990) and/or isolation (Mäki, 1992, 2012). But they may also be created as pure *constructions*, i.e., exaggerated caricatures (Gibbard and Varian, 1978), fictional constructs (Sugden, 2000) or heuristic devices that "mimic [...] some stylized features of the real system"(Morgan and Knuuttila, 2012, p.64). Gilboa et al. (2014) suggested that economic models serve as analogies that allow for case-based reasoning and contribute to the body of knowledge through inductive inference rather than through deductive, rule-based reasoning. We advocate the use of formal, analytic models in this context, because such models allow to make the assumptions transparent that may lead to a proposition and possibly a normative statement upon which a robust theory, and ultimately a robust explanation or prediction can be built. Note that mathematical formalization is a sufficient, but not a necessary prerequisite to develop a formal model, because it allows to precisely formulate its subject domain, making it an "exact science" (Griesemer, 2013, p.299). Moreover, Dasgupta (2002, p.70f) argued that in building a theory "prior intuition is often of little help. That is why mathematical modeling has proved to be indispensible". The analytic approach provides researchers with a toolbox to deal with especially hard and complex problems. By the means of logical verification, propositions can be shown to be *internally* true with regard to the underlying assumption.

In general, the goal of a model is to "capture only those core causal factors, capacities or the essentials of a causal mechanism that bring about a certain target phenomenon"(Morgan and Knuuttila, 2012, p.53). Such an abstraction is the prerequisite for conducting a deductive analysis within a particular scenario of interest. What we consider to be particularly important in order to develop relevant models is that a model's microfoundation should contain elements of both theory and reality. On the one hand, a model's assumptions should reflect *stylized empirical facts* that are well grounded in observed empirical regularities or relevant future scenarios. Such empirical facts can be derived directly from gathered data (most likely with measurement error), may already be the result of extended data analysis, e.g., in the form of detected patterns or correlations, or may be identified by means of a literature review (Houy et al., 2015). However, stylized empirical facts need not (yet) be supported by any theory. This enables us also to incorporate insights of theory-free empirical analysis (particularly (big) data analytics or machine learning) into formal models, which may then lead to a theory that can explain the empirical regularities.[1] On the other hand, a model's assumptions may also be derived from the existing body of knowledge, i.e., from theory. This exemplifies the dual view on the relationship between models and theory: Although models are used to

[1]In this context, it is worth mentioning that although data analytics may be able to predict *what* will happen in a specific context, similar to a theory, it is still theory-free, because it is generally not able to explain *why* it happens. Without theory, however, it must remain unknown whether these predictions can be generalized and and to what extent they are robust to other application scenarios. Therefore, data analytics differs from the traditional paradigm of empirical analysis, which centers around the falsification or validation of hypotheses, which again requires a theory (although not necessarily in the same sense as proposed here - see, e.g., Diesing (2008) for a more elaborate discussion of the relationship between empirical and formal theory) from which these hypotheses are derived in the first place.

advance theory, theory is also used to produce and inform models.

A main line of attack against analytic models is to argue that they are not *realistic* and thus, model-driven theory is useless, because there is nothing to learn about reality. This criticism is amplified in the field of social science, where models are context dependent, as argued above. This naive understanding, however, falls short. First, as we have just mentioned, good models should be grounded in stylized empirical facts. Second, there is an inherent trade-off between accuracy and generality, achieved trough simplicity (Gilboa et al., 2014). Scholars experienced in the domain of modelling generally agree on the fact, that too much complexity in fact impedes the explanatory power and the interpretability of models. For example, Schwab et al. (2011, p.1115) stated that in order "to formulate useful generalizations, researchers need to focus on the most fundamental, pervasive, and inertial causal relations. To guide human action, researchers need to develop parsimonious, and simple models that humans understand". In the words of Lucas (1980, p.697) "a 'good' model [...] will not be exactly more 'real' than a poor one, but will provide better immitations". In this context, the statistician George Box coined the famous phrase that "all models are wrong, but some are useful" (Box, 1979, p.2), clarifying that a model must inherently be *unrealistic* in a dogmatic sense (see Mäki, 2012, for a discussion), but that models in fact enable us to understand *real* phenomena by abstracting from the complexity of reality. To exemplify this, Robinson (1962, p.33) argued that "a model which took account of all the variegation of reality would be of no more use than a map at the scale of one to one". Of course, an interesting model must also exceed a pure tautology, i.e., the results that can be deduced from its assumptions are usually not a priori clear, but may represent surprising results (Koopmans, 1957; Morgan and Knuuttila, 2012). This requirement can be paraphrased by a quote that is supposedly due to Einstein: "Everything should be made as simple as possible, but not simpler".

Furthermore, we wish to emphasize that over and beyond the explanatory function of formal models, the modelling process itself may prove to exhibit value for understanding a particular scenario. Moreover, a model is an instrument to express an individuals' perception of a problem and may therefore serve as a communication device. Gibbard and Varian (1978, p.669) stated that "perhaps, it is initially unclear what is to be explained, and a model provides a means of formulation".

Empirical analyses as the means to evaluate theory According to our theory-centric research view, empirical analysis serves two core functions: i) As described above, empirical analysis is a means to derive stylized facts in order to motivate model assumptions, or likewise, to evaluate the plausibility of proposed assumptions. ii) As will be described next, empirical analysis is also a means to evaluate the quality of a theory as a whole. In the context of IS research, we conceive three main ways in which evaluation of theory can be done.

First, empirical analysis, foremost field and laboratory studies, can be employed in order to to falsify (in the spirit of Lakatos and Popper (Hausman, 2013; Backhouse, 2012)), and more ambitiously to validate, theoretically derived hypotheses. While field studies have the advantage of high external validity, they can be generally challenged on the premises that it is difficult to establish causal effects due to problems of (unobserved) confounding variables and endogeneity. At a fundamental level, this gives rise to doubts whether empirical observations are able to falsify (a fortiori validate) theory at all. These concerns are magnified due to the context-specific nature of field studies and a lack of control over the environment that encompasses investigations. Laboratory experiments may be able to mitigate some of these concerns through systematic variation of treatment conditions, randomization of subjects and augmented control of the researcher. Based on a high internal validity, although at the cost of lack of external validity, isolation of causal relationships is facilitated and falsification of theoretical propositions is more easily justifiable (Guala, 2005). Furthermore, laboratory experiments facilitate the process of de-idealization (Morgan and Knuuttila, 2012), i.e., the generalization of the model context beyond its well-defined assumptions by successively relaxing the assumptions until the theory's established hypotheses begin to break down. Ultimately, however, laboratory and field studies are complementary means to a similar end.

Second, empirical analysis can evaluate the accuracy of theory-driven predictions over time. Although hypotheses may also be regarded as model predictions, the focus here lies less on falsification of suggested causal relationships, but more on the correct qualitative assessment of the impact of future scenarios. With regard to its ability to predict future states of reality (in the sense of Friedman, 1953), a microfounded theory draws from its ability to explain observations at the macro level, based on an understanding of the underlying mechanisms and the necessary conditions. By this means, theory-driven predictions are likely to be more robust to changes of real systems as underlying causes can be identified and theory can be modified accordingly (Dasgupta, 2002). Moreover, formal analysis allows for experimentation and evaluation of counterfactuals. Two remarks should be made in this context: First, it must be noted that there exists an inherent trade-off between a theory's simplicity and its predictive accuracy. While a simple model or theory may apply more generally and is able to make more robust *qualitative* predictions, it will also almost certainly be too simple to make accurate *quantitative* predictions. In turn, the reverse holds true for complex models. This is akin to what is known as the bias-variance-trade-off in statistics (cf. Hastie et al., 2009). Second, even if a theory's prediction may be accurate, this does not "prove" in a deductive sense that it is valid. We may only apply what is known as abductive inference here, that is we can infer that a theory was sufficient to predict the phenomenon of interest, but not that it was necessary, i.e., the only possible theory to be sufficient.

Third, and possibly most interesting in the context of IS research, empirical studies can serve as a testbed for theory-driven design proposals. In this context, laboratory experiments can be seen as an intermediate economic engineering step, similar to a wind tunnel in traditional engineering, where the design proposals (e.g., a proposed market design or regulatory institution) can be evaluated under idealized conditions that mirror those assumptions under which the theory was developed. If the proposed design performs well (relative to the intended goal) in the laboratory then it should be taken to the field for further evaluation. If, however, the proposed design already fails to perform in the laboratory, then there is little reason to believe that it would perform well in the field (Plott, 1987). Consequently, the design, and most probably also the underlying theory, would need revision already at this stage.

3 Conclusions

Recently, several scholars in the fields of management (Locke, 2007; Hambrick, 2007) and IS (Avison and Malaurent, 2014), among others, have criticized excessive adherence to theory and argue that a scientific contribution can also be made without the need for theory. While we are sympathetic with this view, we strongly believe that the development of robust theories is at the core of scientific endeavour. However, we also believe that these models and theories should be both, i) well grounded in stylized empirical facts that are the result of inductive research efforts, as well as ii) evaluated and refined through empirical analyses based on field studies and laboratory experiments. To this end, we have motivated and discussed a microeconomically founded IS research paradigm that we deem suitable to develop theories in our field that are rigor and relevant. In this spirit, we deem the long term goal of microeconomically founded IS research to be the development of robust and stable theories that have been developed and refined through several repetitions of the depicted research process cycle.

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