Communications of the Association for Information Systems

Volume 47 Article 12

11-5-2020

Integrating Explanatory/Predictive and Prescriptive Science in Information Systems Research

Stefan Seidel
University of Liechtenstein, stefan.seidel@uni.li

Richard T. Watson
University of Georgia, rwatson@terry.uga.edu

Recommended Citation

Seidel, S., & Watson, R. T. (2020). Integrating Explanatory/Predictive and Prescriptive Science in Information Systems Research. Communications of the Association for Information Systems, 47, pp-pp. https://doi.org/10.17705/1CAIS.04714

Communications of the Association for Information Systems

Research Paper DOI: 10.17705/1CAIS.04714 ISSN: 1529-3181

Integrating Explanatory/Predictive and Prescriptive Science in Information Systems Research

Stefan Seidel
Institute of Information Systems
University of Liechtenstein
stefan.seidel@uni.li

Richard T. Watson
Department of Management Information Systems
University of Georgia
rwatson@terry.uga.edu

Abstract:

The scholarly information systems (IS) field has a dual role. As an explanatory and predictive science, the field contributes to explaining the pervasive IS that shape the digital age and sometimes also makes predictions about those phenomena. As a prescriptive science, it participates in creating IS-related innovations by identifying means-ends relationships. The two can beneficially interact, such as when explanatory theory provides the basis for generating prescriptions or when applicable knowledge produces explanatory insights. In this commentary, we contribute to integrating these two roles by proposing a framework to help IS researchers navigate the field's duality to extend the cumulative scholarly knowledge that it creates in terms of justified explanations and predictions and justified prescriptions. The process we describe builds on ongoing, dynamic, iterative, and interrelated research cycles. We identify a set of integrative research practices that occur at the interface between explanatory and predictive science and prescriptive science—the explanation-prescription nexus. We derive guidelines for IS research.

Keywords: Explanatory and Predictive Science, Prescriptive Science, Explanatory and Predictive Research, Prescriptive Research, Theory, Innovation, Digital Innovation, Design Science Research.

This manuscript underwent editorial review. It was received 04/29/2019 and was with the authors for seven months for two revisions. Steven Alter served as Associate Editor.

1 The Dual Role of Information Systems Research

The information systems (IS) field has a dual purpose as an explanatory and predictive science (i.e., one that conducts research to create justified explanations and predictions, which researchers typically communicate as explanatory and predictive theories) and a prescriptive science (i.e., one that conducts research to create justified prescriptions about potential solutions, which researchers typically communicate as design principles or design theories)[1]. As an explanatory and predictive science, the IS field contributes to explaining human-initiated phenomena in the form of information systems and sometimes also makes predictions about future events related to those phenomena. As a prescriptive science, it participates in creating information systems that shape the digital age. Studies that exemplify the IS field as an explanatory and predictive science include case studies that explain IT-related change (e.g., Orlikowski, 1993) and studies that conduct experiments to test predictions related to how users interact with information systems (e.g., Hibbeln, Jenkins, Schneider, Valacich, & Weinmann, 2017). Studies that exemplify the IS field as a prescriptive science include action research studies (e.g., Lindgren, Henfridsson, & Schultze, 2004) and design research studies (e.g., Seidel, Chandra Kruse, Szekely, Gau, & Stieger, 2018) that develop and evaluate prescriptions about how one should design information systems.

This duality has been a cornerstone of IS research since its formative years (e.g., Hirschheim, Klein, & Lyytinen, 1995; Keen, 1980; Nunamaker, Chen, & Purdin, 1990; Vogel & Wetherbe, 1984) and has led researchers to develop and appreciate diverse methodological apparatuses for building and testing theories (i.e., developing and justifying explanations and predictions) and for developing knowledge about how one should design and implement information systems (i.e., developing and justifying prescriptions). Yet, while researchers have treated these apparatuses as separate research traditions or even paradigms, the boundaries between them have diminished (Rai, 2018) in IS and elsewhere. Examples include the merging of previously separate apparatuses as in action design research (Sein, Henfridsson, Purao, Rossi, & Lindgren, 2011), the development of designs that juxtapose explanatory modes of inquiry with prescriptive modes (Chatman & Flynn, 2005), the appraisal of programmatic research focusing on theoretical explanation and impact (Nunamaker, Twyman, Giboney, & Briggs, 2017), and even the increasing appearance of single studies that focus on both explanation and prescription, such as where insights gained from an experiment using functional magnetic resonance imaging (fMRI) are used to identify solutions to mitigate the effects of dual task interference (i.e., the performance loss associated with carrying out two tasks at a time) on disregarding security messages (Jenkins, Anderson, Vance, Kirwan, & Eargle, 2016).

We have a central uniting opportunity to blend explanatory and predictive research and prescriptive research. We can facilitate consilience by showing how the two explicitly conceptually connect. Research that has previously discussed integrated approaches to explanation/prediction *and* prescription in IS has 1) been dispersed across specific frameworks such as design science research (Gregor & Hevner, 2013; Walls, Widmeyer, & El Sawy, 1992), action research (Baskerville, 1999; Baskerville & Wood-Harper, 1998), or action design research (Sein et al., 2011), 2) not clearly explained how researchers achieve integration at the level of research practices, and 3) not clearly explained how the two research modes can interact bilaterally and synergistically. We further contend that researchers have relegated most of the actual integration to an implications section in which they primarily focus on explaining and predicting and provide little justification for the prescriptive knowledge they present.

Against this background, we suggest a general framework that integrates explanatory and predictive (such as case study research, survey research, or experiments) and prescriptive (such as design science research, action research, or engaged scholarship) research approaches at the level of research practices and defines measurements for the two key branches. Such a framework will provide researchers with an explicit toolbox to move back and forth between explanatory and predictive research practices and prescriptive research practices and legitimize new forms of hybrid research that involve both types of research practices. Specifically, we describe explanatory and predictive research and prescriptive research processes as ongoing, dynamic, iterative, and interrelated research cycles and, thereby, highlight the tentative and approximate nature of explanatory and predictive knowledge and prescriptive

[1] We use the following nomenclature: a “science” (such as physics, biology, or information systems) involves research practices, and we distinguish between practices that fall into the two categories explanatory and predictive research and prescriptive research (or perhaps into both). As a science, the IS field has a dual role as both an explanatory and predictive science and a prescriptive science and, therefore, also involves both forms of research practice.

knowledge (Dewey, 1938; Habermas, 2003). We also define the explanation-prescription nexus in IS research—a conceptual device to help researchers integrate the two key types of research through their respective primary focus on seeking justified explanations and predictions and generating justified prescriptions. To support cross-paradigm combinative practices (Rai, 2018), the model includes different types of reasoning and different types of research methods.

The issue we highlight engages with the broader debate on how the IS field can maximize its contribution to addressing practical problems (e.g., Grover & Lyytinen, 2015; Gupta, 2017; Rai, 2017; Rosemann & Vessey, 2008). As an applied field, the IS field focuses on deriving general theories about the design, use, and impact of information systems, and practitioners make up a great majority of its members. As academics, we have an opportunity to leverage our research to influence the majority—to paraphrase Archimedes, "Give us good theories and a fulcrum for disseminating them, and we shall move the world". In this view, theory embraces explanation, prediction, *and* prescription—consistent with the idea that theory can not only explain and predict but also prescribe (Gregor, 2006). Theory identifies the relationship between critical concepts to provide a sense of understanding and sometimes make predictions *and* to create applicable knowledge by making prescriptions about solutions to improve practice. Theory building represents an "endless approximation" of successive conceptual improvements to advance understanding and explanation of a phenomenon (Churchman, 1971) and, ultimately, to improve practice.

We proceed as follows: in Section 2, we present science's key goals in terms of explanation, prediction, and prescription, how researchers across fields have discussed them, and how they currently apply to the IS field. In Section 3, we consider the pathways of both types of research and, thereby, highlight their fundamental nexus. Our conceptual framework reconciles the lexica that explanatory and predictive research and prescriptive research use, proposes models describing their pathways, and juxtaposes the two cultures to develop an integrated model that highlights their relationship. In Section 4, we illustrate the interplay between the two types of research using three published examples. In Section 5, we further apply the socio-technical[2] systems lens to discuss the limits of predictive and prescriptive accuracy when studying information systems. In Section 6, we develop specific guidelines for integrating the two modes of research in the IS field. Finally, in Section 7, we conclude the paper.

2 Research Background

2.1 The Key Goals of Scientific Research: Explanation/Prediction and Prescription

Science has traditionally focused on explaining and predicting phenomena (Singleton & Straits, 2010; Von Wright, 2004) using labels such as basic science (Stokes, 1997), simply sciences (Simon, 1996; Snow, 1959), or behavioral research (Hevner, March, Park, & Ram, 2004; Rai et al., 2017). Still, many clearly expect science to not only provide explanations and predictions but also say something about how things *ought* to be (i.e., about making prescriptions) using labels such as applied science (Shneiderman, 2016; Stokes, 1997), technological innovation (Stokes, 1997), sciences of the artificial (Simon, 1996), and design science research (Hevner et al., 2004; Rai et al., 2017). In this section, we briefly introduce the key goals that explanation and prediction on the one hand and prescription on the other focus on, and we distinguish two complementary modes of scientific inquiry: explanatory and predictive research (focuses on generating explanations and predictions) and prescriptive research (focuses on generating prescriptions). Researchers typically present explanations, predictions, and prescriptions as theory. Here, theories refer to "abstract entities that aim to describe, explain, and enhance understanding of the world and, in some cases, to provide predictions of what will happen in the future and to give a basis for intervention and action" (Gregor, 2006, p. 616).

[2] One can view organizations as work systems that comprise tasks, structures, people, and technologies (Bostrom & Heinen, 1977a). One can also view information systems themselves as socio-technical systems that store, process, and disseminate information (Piccoli, 2012) as they help individuals, groups, and organizations accomplish their goals (Watson, 2014). IS scholars have used different notions such as materiality (Leonardi, 2011; Scott & Orlikowski, 2012) or technical object (Markus & Silver, 2008) to describe the technology component in socio-technical systems. Thus, theorizing on information systems and organizational change in particular addresses the relationships between "the social" and "the material" in the organizing context (Leonardi, 2011; Orlikowski, 1992). In this paper, we use the vocabulary that concurs with the socio-technical view that involves people, tasks, information technologies (i.e., representing materiality), and structures. We argue that this vocabulary is sufficiently abstract to discuss the key phenomena that the IS field focuses on (Leonardi, 2012).

Explanation is associated with human understanding as explanations can help by "inducing a subjective state of understanding in an individual" (Gregor, 2006, p. 617). Explanations often use causal mechanisms/causal processes (such as law-like generalizations, empirical rules, statistical associations, or teleological-type causes) to provide a rationale for a phenomenon (Gregor, 2006; Reynolds, 1971; Singleton & Straits, 2010), but researchers have also argued that the key for explanation are relationships, or sequences of events, not causality (Dubin, 1969). Causality requires a change in one event (the cause) to at least partially contribute to change in another event (the effect) (Singleton & Straits, 2010). The cause must precede the effect and one must rule out alternative causes that might have created the effect. Notably, however, in the social sciences, explanations do not necessarily provide cause-effect relationships that allow one to make predictions and to quantitatively test them. Prominent examples include practice views such as structuration theory and its derivatives (Giddens, 1984; Orlikowski, 1992).

Predictions forecast future observations based on input values (Shmueli, 2010). Prediction and explanation go hand-in-hand when an explanation provides causal mechanisms that can be invoked to make predictions (Singleton, McLean, & Altman, 1988). Understanding underlying causal processes can lead to more accurate and more useful predictions (Reynolds, 1971; Singleton & Straits, 2010, p. 26). However, predictions often remain a distant goal when researchers seek to explain a socio-technical system.

Prescriptions—and, hence, prescriptive models—involve variables that can be changed or controlled (Simon, 1990). Based on this view, prescriptions refer to statements about what should be done (i.e., the means) in order to accomplish an outcome (i.e., the ends), which broadly means "not just seeing what is but changing what we see" (Pearl, 2018, p. 56)[3]. In the context of scientific inquiry, we see prescriptions as statements about applying one or more concepts in a coordinated and integrated fashion (i.e., the means) to accomplish purposive change (i.e., ends). In IS, prescriptions pertain to designing and using information systems (i.e., they concern how one should design certain systems or how one should use these systems to accomplish a goal).

To summarize, **explanatory and predictive** research seeks to generate explanations that can enhance understanding and, in some cases, also to generate predictions about future events. **Prescriptive** research then uses the explanatory and predictive models as a logical nexus for developing prescriptions about the means that lead to realized desired outcomes. At the same time, prescriptively designing information systems informs causal analysis (Gregor & Hovorka, 2011) and can, thus, lead to improved explanation and prediction.

The IS field has seen its role as both an explanatory and predictive and a prescriptive science since its inception (Hevner et al., 2004; Keen, 1981; Mumford, Hirschheim, Fitzgerald, & Wood-Harper, 1985; Rosemann & Vessey, 2008). We summarize the goals that explanation and prediction and prescription primarily focus on in Table 1.

At least for the past few decades, scholars across scientific fields have increasingly agreed that we should not divorce these two key research types but rather exploit their complementary power (Arthur, 2009; Shneiderman, 2016; Stokes, 1997). Basic science provides understanding that can lead to practical application and innovations. Use can stimulate basic science research when an application fails to deliver partially or fully a theory's promise. As understanding and use are deeply interwoven, partnerships between practitioners and researchers can prove mutually beneficial (e.g., Ford et al., 2003; Van de Ven, 2007). Accordingly, various scholars have called for a greater focus on actionable outcomes rather than *solely* advancing understanding (Bailey & Eastman, 1996; Lawrence, 1992; Pfeffer & Fong, 2002; Weick, 1989).

[3] Pearl (2018) succinctly describes such statements about interventions as "The probability of event Y = y, given that we intervene and set the value of X to x and subsequently observe event Z = z" (p. 56).

Table 1. Primary Goals of Explanatory/Predictive Research and Prescriptive Research

	Concept	Definition
Explanatory and predictive research goals	Explanation	Explanations create understanding often through specifying causal mechanisms or processes. • Explanatory models can take different forms that range from process theories that provide explanation without propositions (Pentland, 1999), such as practice-based views (Bourdieu, 1977; Giddens, 1984), to variance models that provide explanation by means of propositions that one can test using statistical methods (Shmueli, 2010). • Models that provide causal explanation also have predictive power (Shmueli, 2010).
	Prediction	Predictions forecast future observations based on input values. • Predictive models can come in different forms, such as Bayesian, parametric or non-parametric, data-mining algorithms, or statistical models (Shmueli, 2010). • Prediction and explanation go hand-in-hand if an explanation provides causal mechanisms that one can invoke to make predictions (Singleton et al., 1988). • While models that provide causal explanation have predictive power, there are also predictive models that do not provide causality (Gregor, 2006; Reynolds, 1971; Shmueli, 2010), such as neural nets. • In cases where researchers develop process theory (Markus & Robey. 1988) or systems theory (Churchman, 1971), prediction is more difficult; still, such theory can inform the development of further explanations and predictions.
Prescriptive research goals	Prescription	Prescriptions refer to statements about applying one or more concepts in a coordinated and integrated fashion (means) to accomplish purposive change (ends). • Prescriptive models include variables that can be manipulated; that is, one can turn predictive models into prescriptive models (Simon, 1990). • Prescriptive statements aim at utility; that is, a desirable outcome (Goldkuhl, 2004). • One can turn models that contain controllable variables into statements that give explicit advice (Goldkuhl, 2004), which researchers have called design principles (Gregor, Chandra Kruse, & Seidel, forthcoming; Sein et al., 2011) or principles of form and function (Gregor & Jones, 2007).

2.2 The Integration of Explanatory/Predictive and Prescriptive Research in IS

In IS, we can trace the debate on the field's dual role to its early years (Keen, 1980; Nunamaker et al., 1990). More recently, IS scholars have drawn attention to how the IS field might improve its impact (Goes, 2014; Grover & Lyytinen, 2015; Gupta, 2017; Rai, 2017; Rosemann & Vessey, 2008). Clearly, what stakeholders see as a valuable contribution depends on their various goals and the current discourse in the field (Bichler et al., 2016), and we can measure scientific contributions along dimensions such as aesthetics, scholarly value, and practical utility (Rai, 2017). Contributions in an academic field must have scholarly value (Rai, 2017) and should also provide societal benefits by developing and rigorously validating solutions, such as information systems to facilitate social improvement (Giboney, Briggs, & Nunamaker, 2016) and a better world (Walsham, 2012).

IS scholars consider behavioral science that focuses on developing and testing explanatory and predictive theory (aiming at approximating truth) and design science research that focuses on developing and testing concrete information systems or design theories about the development of information systems (aiming at utility) complementary approaches (Gregor & Hevner, 2013; Gregor, Müller, & Seidel, 2013; Hevner et al., 2004). Explanatory theory can provide the basis for prescriptive knowledge: 1) in some cases, one can translate explanatory causality statements into prescriptive statements; and 2) effects in explanatory statements can correspond to goals in prescriptive statements (Goldkuhl, 2004). Thus, explanatory theory provides justificatory knowledge for prescriptive knowledge (Gregor & Jones, 2007; Walls et al., 1992).

An integrated view of IS as both an explanatory and predictive science and a prescriptive science is 1) independent of specific methods/approaches and 2) explicit about integrating the two research types at the level of research practices that can help our field advance to satisfy objectives related to both understanding and use. To unpack the specific relationships between the two research modes and to proceed to an integrated IS model that embraces both, we review the pathways to each and then suggest their integration at the level of research practices.

3 Conceptual Model for Integrating Explanatory/Predictive and Prescriptive Research in IS

While our suggested integration includes different types of research methods, we make some basic assumptions. Most importantly, we assume scientific knowledge's *fallibility* (i.e., that no justification process that guarantees truth exists) (Peirce, 1955). Thus, we take a dynamic view of research practices where knowledge is intermediate and an approximation to truth (Dewey, 1938; Habermas, 2003). One requires such a perspective when studying emergent and evolving socio-technical phenomena as with the IS field. Such phenomena evolve dynamically, and, consequently, explanatory, predictive, and prescriptive knowledge are necessarily incomplete and tentative and evolve dynamically. Following Dewey (1938), we suggest that we need to judge scientific discovery's outcomes based on the scientific practice's "ends in view" (i.e., those standards that provide the starting point of a research process be it with the goal to explain, predict, or prescribe—or any combination of them).

Following from this view, we conceptualize both explanatory and predictive science and prescriptive science as ongoing and interrelated research cycles that focus on developing increasingly complete and accurate explanatory and predictive knowledge or prescriptive knowledge, respectively. We separately discuss the two research modes before we address their integration. We highlight specific challenges in integrating them due to their diverse goals and associated conceptual differences (Stokes, 1997).

3.1 The Explanatory and Predictive Research Cycle

The concept of basic science epitomizes the idea of increasing human understanding by developing justified explanations that might also predict future events (Stokes, 1997). While explanation does not allow for prediction in some cases (Gregor, 2006), research aiming at explanation commonly aims at developing knowledge that has also high predictive accuracy; that is, the conceptualization's "ability to generate accurate predictions of new observations, where *new* can be interpreted temporally…or cross-sectionally" (Shmueli & Koppius, 2011, p. 555). In their study on healthcare predictive analytics, for instance, Lin, Chen, Brown, Li, and Yang (2017) highlight how electronic health records offer a basis for risk profiling in chronic care with high predictive accuracy. However, despite such successful applications, in the social sciences, predictive accuracy often remains a secondary goal. Organizational life's complexity makes predictive accuracy a distant goal in many situations, especially for phenomena subject to continual and complex change where little opportunity exists to study equilibrium states as is often the case in IS. We summarize explanatory research goals and methods in Table 2.

Table 2. Explanatory and Predictive Research: Goals and Methods

Primary goals	Explanatory research focuses on increasing understanding by developing justified explanations that may also be suitable for prediction (Gregor, 2006).
Measurement of outcome	If a theory resulting from explanatory research makes no predictions, its outcomes can be measured in terms of *explanatory power* (i.e., how well the theory explains observations). If the theory provides predictions, it can be measured it in terms of its *predictive accuracy*, a conceptualization's ability to accurately predict new observations; one may interpret "new" both temporally and cross-sectionally (Shmueli & Koppius, 2011).
Example methods	Constructing/testing explanation: case studies, field studies, grounded theory research, questionnaires, literature review, survey research
IS example	Leonardi's (2011) imbrication model, which he grounds in a case study, explains how material and social aspects are interwoven in the creation of organizational change; processual theory that does not provide testable propositions; that is, explanation but not prediction.

There are differing positions on—and possibilities for—where and how explanatory and predictive research should start, such as through observation and inductive and abductive reasoning to move towards theory (e.g., Glaser & Strauss, 1967) or through the formulation of propositions based on logical deduction (e.g., Popper, 2002). Researchers commonly emphasize either *theory development* (such as through case study research) or *theory testing* (such as through experiments or surveys), though they sometimes emphasize both. Still, we can identify several key elements (see Table 3) that different types of research include and emphasize to a varying degree (e.g., Handfield & Melnyk, 1998; Recker, 2013).

Table 3. Explanatory and Predictive IS Research: Key Concepts and Research Activities

Concept	Definition	IS research
Observation	Observation occurs when a person becomes sensitized to a phenomenon or problem and pays attention to its major characteristics.	Observation in explanatory and predictive IS research typically involves paying attention to the development, use, involvement, and consequences of implementing an IS.
Description	Description describes an observation in the form of, for example, text, quantitative data, or visualization.	Description in explanatory and predictive IS research involves describing IS phenomena via text, quantification, and, more recently, trace data that provide detailed and time-variant accounts about how stakeholders use IS.
Conceptualization	Conceptualization transforms a description into concepts and a succinct statement of relationships, such as a framework, a variance model, or a process model.	Conceptualization in explanatory and predictive IS research relates to both social and technical aspects of information systems.
Explanatory/predictive knowledge	Researchers typically package explanatory and predictive knowledge as explaining or predicting theory (i.e., as an integrated set of relationships that explain/predict a phenomenon). Such theory can come in different forms—most notably variance and process theory.	Explanatory and predictive knowledge in IS involves concepts and relationships that represent both social and technical aspects and their interactions.
Theoretical proposition	Theoretical propositions refer to relationships between concepts. They provide the basis for developing hypotheses to test a theory.	In explanatory and predictive IS research, researchers often present propositions as relationships between concepts where one or multiple concepts represent information systems or aspects of information systems.
Evaluation/testing	Evaluating theory using qualitative and quantitative techniques.	In explanatory and predictive IS research, researchers traditionally work with latent variables that represent social or technical aspects. Evaluation/testing generates new observations that can induce a new explanatory and predictive research cycle or perhaps lead into a new prescriptive research cycle.

Researchers use **observation** either to develop understanding (e.g., through a case study), to justify existent explanation and prediction (e.g., through empirical testing), or both (e.g., in the case of grounded studies where researchers ground explanation in data). A new stream of research may start with observation—when researchers become sensitized to a phenomenon or problem and pay attention to its major characteristics. Observation in the IS field typically involves paying attention to IS phenomena such as the development, use, involvement, and consequences of information technology in some social, often organizational, context and, thus, often involves both social and technical aspects. Throughout their observation, researchers can draw on different approaches to collect qualitative and quantitative data, such as interviews (as in a case study on IT-related change (Orlikowski (1993)), experiments that generate quantitative data (as in a study on the relationships between mouse movements and user emotions (Hibbeln et al., 2017)), participant observation (Myers, 1999), or surveys (e.g., the annual Society for Information Management key issues study and its national variants). Recently, researchers have increasingly collected and used naturally occurring digital trace data as a key process in observing IS-related phenomena in order to develop theory (Berente, Seidel, & Safadi, 2018).

Researchers turn observational data into **description**, which they need to either move towards an explanation or prediction or to evaluate/justify an existent explanation or prediction. Description constitutes a method for compacting observation data to capture their essence. Thus, researchers might describe quantitative findings in terms of statistical measures and a series of interlinking actions in terms of a textual or visual description of a process. IS researchers use various ways to describe IS and related phenomena, such as textual descriptions of case studies (e.g., Orlikowski, 1993), quantification, and increasingly also information in the form of trace data providing detailed, time-variant accounts of how information systems are used (Berente et al., 2018).

This description can then provide the basis for **conceptualization** where researchers gradually move from observational facts to more general concepts that capture a phenomenon's essence. Alternatively, they may use concepts from the existing literature. Concepts represent multiple observed instances, can be more or less abstract (i.e., depend more or less on specific times and places), and relate to one another through relationship statements (Reynolds, 1971).

Concepts succinctly describe core features for understanding a phenomenon and, thus, provide the basis for developing **explanatory and predictive knowledge**, which often comes packaged as explanatory and predictive theory (Gregor, 2006). Broadly, theories refer to well-developed relationship statements that explain or predict phenomena. Thus, they can take different forms, such as a variance model (e.g., Delone and McLean's (1992, 2003) model of IS success), a process model (e.g., Orlikowski's (1993) model of CASE tool adoption), or a systems model that describes key components and their interrelationships (e.g., the layered modular architecture that Yoo, Henfridsson, and Lyytinen (2010) describe). Burton-Jones et al. (2014) describe these three theoretical perspectives in detail.

Theories may comprise **theoretical propositions** that provide the basis for deriving measurable and testable **hypotheses** and evaluating/justifying them by further systematic observation. In IS, propositions refer to relationships between concepts where one or multiple concepts typically represent information systems or aspects of them, and hypotheses are their measurable and testable counterparts. Thus, propositions and hypotheses in IS typically describe the interrelationships between social and technical aspects. Justifying an explanatory and predictive theory requires one to discover confirming evidence. In applying nomothetic methods, discovering such evidence may involve recurrently testing hypotheses that the researcher generates from the theory to establish its valid boundaries. In applying idiographic methods, discovering such evidence may involve providing clear chains of evidence, considering alternative viewpoints, and corroborating findings (although, in this latter case, the boundaries of the substantive circumstances that researchers study typically confine their findings, which limits the potential to predict future events). Note that researchers often have no formal propositions to justify (and, thus, also no hypotheses to test), such as in situations where they develop process theories, but they may compare a process model to empirical data.

During the justification process, researchers will likely revise and elaborate on the original theory. Alternatively, they may disband the theory, which involves subsequent description, conceptualization, and integration of that conceptualization in new or revised explanatory and predictive knowledge. Still, there is no state in which we can consider a theory "final"—every explanation remains tentative. Figure 1 (next page) visualizes the cyclic, iterative nature of these explanatory research activities.

This process's cyclic nature highlights knowledge generation's tentative nature (Dewey, 1938; Peirce, 1955). Throughout the phases in this research cycle, one can apply different types of reasoning. New theorizing might originate from a "creative spark", while careful observation, description, and subsequent conceptualization might inform it. While moving from observation to description and conceptualization primarily constitutes an **inductive** process (Handfield & Melnyk, 1998; Singleton & Straits, 2010), researchers often apply **abductive** reasoning to find the most plausible explanation for an observation (Aliseda, 2006; Peirce, 1997). We find **deductive** reasoning mostly when researchers test theories by comparing the predictions of their hypotheses (i.e., what the observations should be in case the theory is correct) to the actual empirical evidence, which leads to a decision to accept or reject a hypothesis (Handfield & Melnyk, 1998).

3.2 The Prescriptive Research Cycle

Prescriptive research focuses on developing justified prescriptions about what one should do to accomplish a desirable outcome and, thus, on means-ends-relationships. As such, it concurs with the concept of applied science, which focuses on use (Stokes, 1997) or solutions (Shneiderman, 2016), and with the sciences of the artificial, which focus on human-made systems (Simon, 1996). These prescriptions—in analogy to explanations and predictions—qualify as scientific knowledge because they result from applying a rigorous process that we outline in this section and because they typically do not pertain to one particular situation but to various situations that share the same boundary conditions.

For instance, a set of design principles for sensemaking support systems says something about how one should design a class of information systems that help people understand complex issues in an organization (Seidel et al., 2018). A set of patterns for object-oriented software development represent prescriptions that help create software more efficiently (Gamma, 1995).

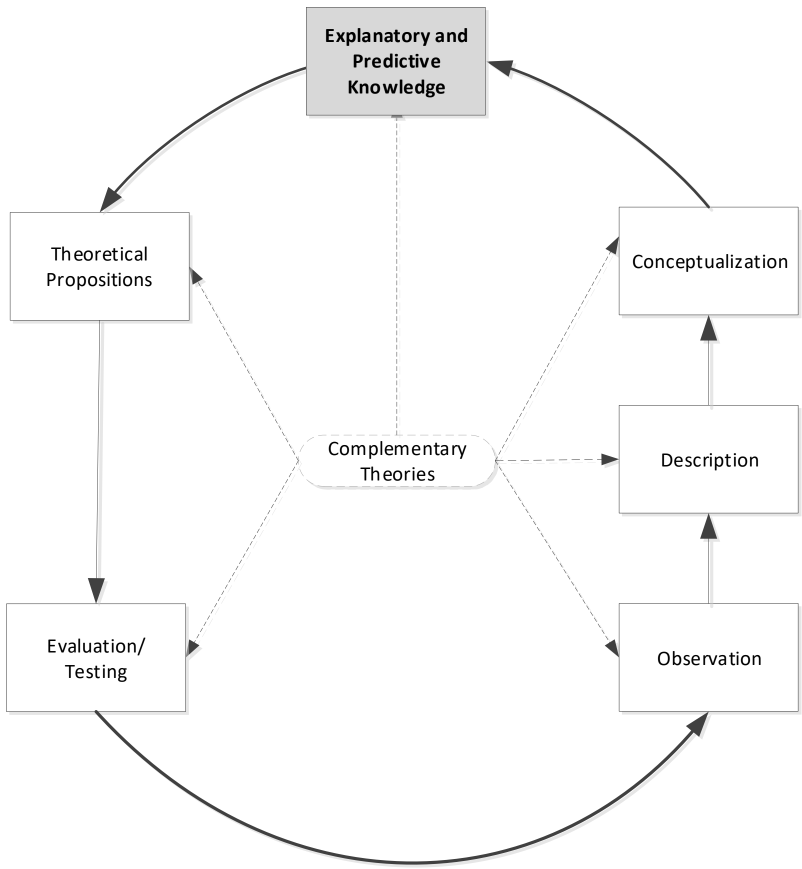

Figure 1. The Typical Explanatory and Predictive Research Cycle

Ultimately, researchers desire high prescriptive accuracy. We can define prescriptive accuracy based on how Shmueli and Koppius (2011) explain predictive accuracy that we present in Section 3.1. In this view, researchers apply prescriptions in order to achieve a certain outcome, and prescriptive accuracy refers to a conceptualization's ability to generate solutions (i.e., the means) that, if implemented, produce outcomes (i.e., the ends) with high predictive accuracy. Thus, one can transform prescriptive statements into propositional statements and then test them empirically once they have been operationalized and, thus, turned into hypotheses.

Still, while researchers often desire prescriptive accuracy, prescriptions are always tentative. Further, as predictive accuracy has limits, so too does prescriptive accuracy. As a consequence, prescriptive research primarily attends to utility rather than to seek the best solution (Hevner et al., 2004)—still, most would agree that prescriptions should ultimately work with high accuracy levels.

Thus, researchers must codify prescriptions to communicate knowledge about the outcomes of actions that one should take or the solutions that one should implement, which compares to the codified propositions we find in explanatory and predictive theory (Gregor & Jones, 2007; Gregor et al., 2013; Hevner et al., 2004). In contemporary IS research, researchers often capture prescriptive knowledge through design principles (Gregor et al., forthcoming) or design theories (Gregor & Jones, 2007; Walls et al., 1992; Walls, Widmeyer, & El Sawy, 2004) that often state how one should design classes of information systems. Design theories reflect prescriptive knowledge mostly in two components (Gregor & Jones, 2007). First, design theory may contain testable propositions that comprise controllable variables that one can change (Simon (1996) calls these "command variables") and that represent the suggested means. Second, design theory's principles of form and function are normative statements that inform how one should create the solution. A design theory for creativity support systems, for instance, contains both propositions that involve controllable variables and statements about designing instances of that class of systems (Müller-Wienbergen, Müller, Seidel, & Becker, 2011). Table 4 summarizes prescriptive research goals and methods.

Table 4. Prescriptive Research: Goals and Methods

Primary goals	Prescriptive research focuses on developing justified prescriptions about what one should do to accomplish a desirable outcome. Thus, prescriptive research focuses on generating prescriptive knowledge, which researchers typically present as design theory (Gregor & Jones, 2007; Walls et al., 1992; Walls et al., 2004) or design principles (Gregor et al., forthcoming).
Measurement of outcome	Prescriptive research focuses on delivering utility with high prescriptive accuracy. *Prescriptive accuracy* refers to a conceptualization's ability to generate solutions ("means") that, if implemented, produce outcomes ("ends") with high predictive accuracy.
Example methods	Constructing/testing prescriptions: design science research approaches, action research, action design research, Experiments for testing interventions, field experiments
IS example	IS can mitigate dual task interference (DTI)—the cognitive limitation that involves performance loss when one simultaneously performs two tasks (Jenkins et al., 2016).

While prescriptive research follows a similar pathway as explanatory and predictive research, they still differ, and IS scholars have suggested different process models, such as in design science research (e.g., Kuechler & Vaishnavi, 2012; Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007) and action research (Baskerville, 1999) for prescriptive research. While research that focuses on explanation often starts with observing a phenomenon, prescriptive research often starts with **observing** a problem (Peffers et al., 2007; Sein et al., 2011). Researchers turn these observations into **descriptions** that may, for instance, analytically decompose the problem to identify a potential solution's requirements (Peffers et al., 2007). Decades of research and practice in software engineering, for instance, have produced a vast body of prescriptive knowledge on formulating and translating these requirements into software (e.g., Pressman, 2005). The problems perceived in practice provide "impetus for formulating the research effort" (Sein et al., 2011, p. 40).

This description can then provide the basis for **conceptualization** where researchers turn the description of problem and requirements into concepts. In their anatomy of a design theory, Gregor and Jones (2007) call these concepts constructs and define them as "representations of the entities of interest in the theory" (p. 325).

Concepts, in turn, provide the building blocks for developing **prescriptive knowledge**. Design principles, for instance, are normative statements that say something about how one should design (Gregor et al., forthcoming; Gregor & Hevner, 2013) or use certain systems or, more broadly, should do something (Goldkuhl, 2004)—similar concepts include technological rules (Bunge, 1967) and technical norms (Niiniluoto, 1993). These normative statements say what to do (i.e., the means) in order to accomplish some outcome (i.e., the ends), and it is possible to transform these statements into propositional statements that one can evaluate (Goldkuhl, 2004; Gregor & Jones, 2007). Statements that include controllable variables allow researchers to test interventions through experiments (Simon, 1990). The aforementioned design patterns for object-oriented software development (Gamma, 1995) exemplify prescriptions. Design principles are a form of nascent design knowledge that provides the basis for full-blown design theories (Gregor & Hevner, 2013), which we can conceive of as systems of design principles.

In order to be able to evaluate the prescriptive statements, researchers need to create an empirical situation to generate data. First, they move into the **design** stage—that is, describing a system (i.e., the means) to produce certain outcomes (i.e., the ends) (Gero, 1990; Simon, 1996). For instance, in action design research (Sein et al., 2011), they develop an IS-related intervention to remedy a problem. Experimental research has particular relevance in the prescriptive research context as it can help researchers test the effects of a particular solution, such as an IS intended to change a group's or actor's behavior (Jenkins et al., 2016).

In order to generate empirical observations to evaluate a design, researchers further need to **implement** it. In action design research, for instance, researchers implement their solution in an organizational setting and collect observational data about the effects and, thereby, close the cycle to observation. Evaluating these effects requires researchers to explicitly define evaluation goals (Venable, Pries-Heje, & Baskerville, 2016). For instance, in studying IS service quality, Watson, Pitt, and Kavan (1998) implemented and analyzed several actions to determine how the actions improved service quality. Thus, in action design research and design science research in general terms, the notion of research cycles has unsurprisingly gained prominence (Hevner et al., 2004; Sein et al., 2011).

Similar to the explanatory and predictive research cycle, any prescription is tentative and will likely be revised and elaborated on or may even be disbanded upon evaluation (Venable et al., 2016). If the original prescription is sound, the justification process will steadily increase the prescriptive accuracy by rigorously accumulating supporting evidence across contexts and time (see Figure 2).

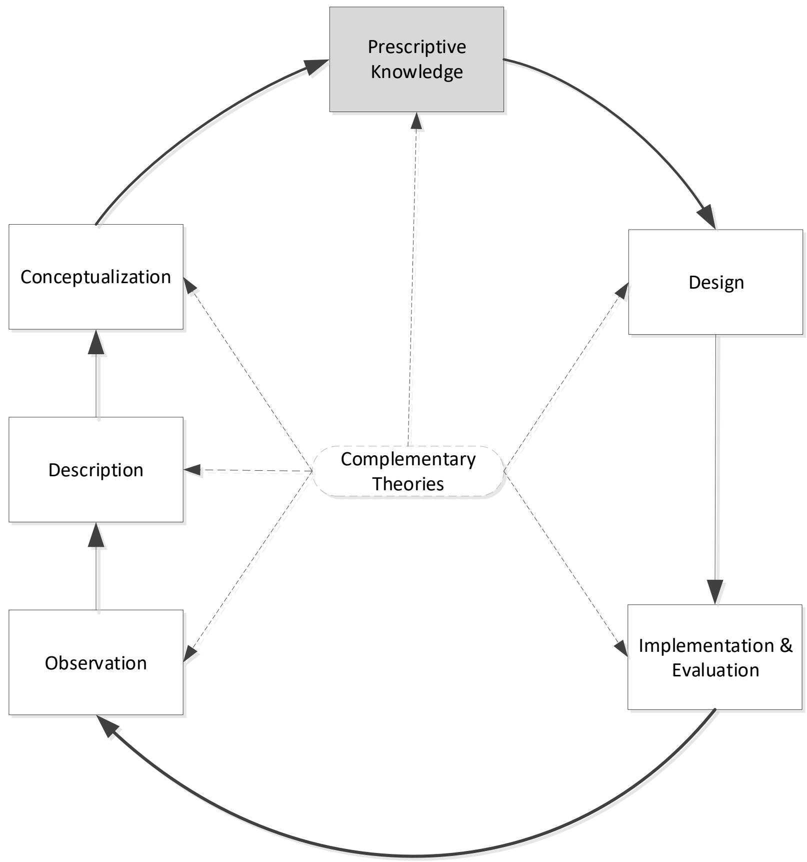

Figure 2. Prescriptive Research Cycle

Prescriptive research—like predictive and explanatory research—constitutes a cumulative endeavor that focuses on iteratively increasing a prescription's accuracy, which justifies its continuing existence as the cyclical order of the key steps in Figure 2 indicates. Moreover, researchers apply the same types of reasoning (i.e., inductive, abductive, and deductive).

Table 5 summarizes the key concepts in prescriptive research. Notably—as in explanatory and predictive research—researchers can enter the cycle at any stage. Sometimes an elucidating thought might inform design, then researchers might implement it, and observation may yield insight that eventually leads to conceptualization and may, in turn, even inform explanatory and predictive research. Experimentation rather than theoretical work might characterize new topic areas in particular as with research on decision support systems, which has traditionally been an application area of design science research (Arnott & Pervan, 2005, 2012, 2014; Power, 2007).

Table 5. Prescriptive IS Research: Key Concepts and Activities

Concept	Definition	IS research
Observation	Observation occurs 1) when researchers become sensitized to a problem situation or 2) when they find a novel solution to a problem. Observation can both provide the ground for developing concepts and propositions and for evaluating/testing propositions.	Observation in prescriptive IS research typically involves paying attention to situations with no solution or an unsatisfactory solution as measured by some performance standard.
Description	Description describes an observation in the form of, for example, text, quantitative data, or visualization.	Prescriptive IS research focuses on not only a black-boxed solution's consequences but also its specific and general features (i.e., the requirements) that bring about an effect or that change a social process.
Conceptualization	Conceptualization transforms a description into concepts and a succinct statement of relationships. Normative statements say how one should do things, which can be translated into predictive models.	In prescriptive IS research, such conceptualization involves constructs (Gregor & Jones, 2007) that represent the solution.
Prescriptive knowledge	Prescriptions concern the means (processes, methods, or systems) that can bring about an envisioned outcome (the ends).	In prescriptive IS research, prescriptions involve some type of IS-related solution and expected outcomes.
Design	Researchers need to turn prescriptions into designs in order to evaluate the prescriptions' utility and accuracy.	In prescriptive IS research, in order to evaluate/test a prescription, researchers must devise a specific design. This design bridges the abstract prescription and the concrete implementation.
Implementation and evaluation	Implementations are instantiations of designs.	Implementation generates observations for evaluation. These observations can then induce a new prescriptive research cycle or perhaps lead to an explanatory and predictive research cycle.

3.3 Integration: The Explanatory-Prescriptive Research Nexus

Both research modes frequently draw on the scientific body of knowledge for various activities such as data collection and analysis—they use complementary theories (see Figure 3). For example, research that focuses on developing explanatory and predictive theory might draw on theories of research design, data collection, and data analysis. Similarly, a prescription researcher might seek guidance from theories of design, participant observation, and statistical analysis. While researchers might primarily focus on developing and justifying explanatory, predictive, or prescriptive knowledge, they also have the possibility to contribute to complementary theory development. Explicating the complementary theories that informed a research process creates transparency about the scaffolding researchers used to conduct both forms of research and constitutes a necessary step to contribute to academia or practice.

Notably, Figure 3 describes an idealized process for both research types and their interactions. In conducting research, researchers will often implement only a subset of the suggested elements, and by no means do we intend our model to straightjacket researchers. For instance, case study researchers may move from observation to description to conceptualization but perhaps not to developing full-blown theory and most certainly not to testing that conceptualization (at least not in the same paper).

Explanation, prediction, and prescription have closely intertwined goals, and we can identify important connections between them: the observation, the description, and conceptual nexuses (see Table 6). We do not focus on exhaustiveness but rather present an extensible general model.

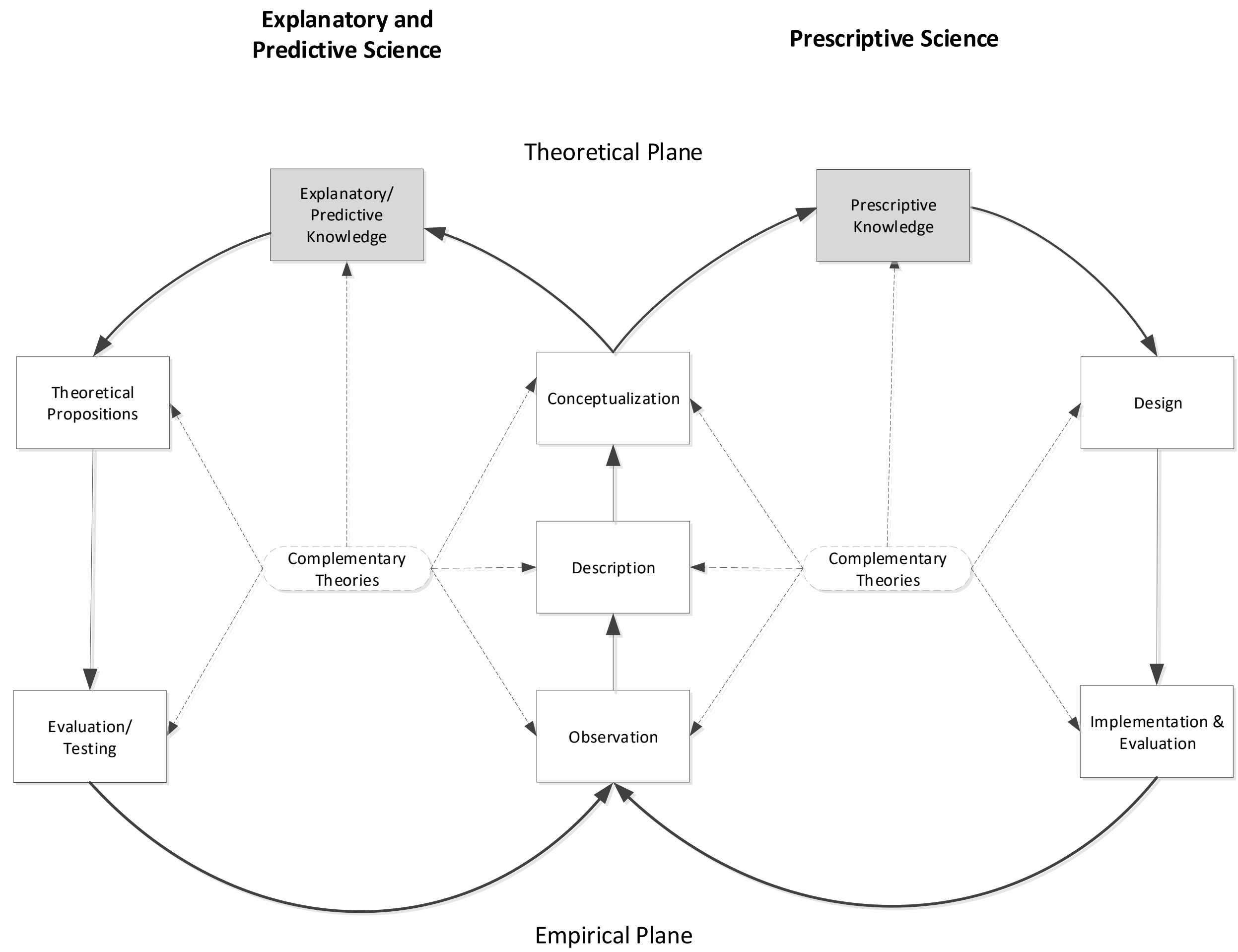

Figure 3. Integrating Explanatory/Predictive and Prescriptive Research

Table 6. Research Nexuses

Nexus	Description
Observation nexus	Observations in IS entail both social and technical aspects of information systems depending on the observer's sensitization. They serve as a point of connection between identifying concepts for explanation or prescription.
Description nexus	Researchers turn observations into descriptions; they must decide whether to focus on descriptions that prepare the ground for explanation (e.g., focusing on a narrative that may eventually allow for processual theory) or prescription (e.g., a problem situation and requirements that a solution might address). Often, the same description can provide paths towards explanation/prediction and prescription.
Conceptual nexus	Conceptual inference: explanatory theory can provide the basis to identify suitable means through a process of conceptual inference whereby researchers infer potential solutions based on an explanatory model's causal variables. Similarly, accounts of practical solutions can help researchers identify cause-effect relationships as, for instance, researchers can represent the solution through a causal variable. Conceptual integration: researchers introduce controllable variables into predictive models.

Observations have a central role in empirical research as they provide both the motivation for developing conceptualizations and the reference by which researchers test and refine existent conceptualizations. Thus, observation and description can help researchers develop explanations, predictions, and prescriptions—and researchers need to test them all via further rigorous observation. The same field case can form the basis for developing explanatory and predictive theory or prescriptive theory (or perhaps both). For instance, researchers could use data on individuals' reactions to security messages that they collected through an fMRI to 1) explain why and under what circumstances individuals disregard security messages and 2) to design solutions that mitigate this effect (Jenkins et al., 2016). This **observation nexus** appears commonly in both types of research and relies on common complementary observation theories. Further, researchers determine the specific stance (i.e., explanatory and predictive or prescriptive) by how they frame the research issue because it sensitizes them to look for certain features and outcomes. The theoretical and methodological lenses that researchers choose impact what they observe.

Researchers turn observations into descriptions that may lend themselves towards explanation and prediction or prescription. Exploratory case studies, for instance, typically constitute descriptions that prepare the ground for explanation and, in some circumstances, predictions related to a phenomenon of interest. In an action research study, however, researchers may study a hitherto-unsolved organizational problem and provide the foundation to identify a solution. In a later stage, the same prescriptive researchers may attend to a first version of that solution and analyze how it provides outcomes that alleviate the problem situation and how one might improve this solution. Again, this **description nexus** appears commonly in both types of research. Often, the same description can provide an impetus for developing explanatory and predictive or prescriptive statements.

At the conceptual level, explanatory statements can inform prescriptive statements, and prescription can lead to novel theoretical explanations and predictions—the **conceptual nexus**. In design science research, explanatory and predictive theory can provide the foundation to derive prescriptions (Gregor, 2006; Walls et al., 1992; Walls et al., 2004). Technologies harness and exploit one or more effects or principles (Arthur, 2009), and revealing those effects provides the basis for devising appropriate means. Kernel theories (Gregor, 2006; Kuechler & Vaishnavi, 2012) inform the design of purposive systems (Hevner et al., 2004; March & Smith, 1995) intended to produce a desired practice effect.

Researchers can integrate both types of research in their research practice. Explanatory and predictive theory can provide the basis to identify practical solutions through a **conceptual inference** process whereby researchers infer potential solutions based on an explanatory model's causal variables (in the case of variance theory) or processual elements that explain how events unfold (in the case of process theory). Similarly, accounts of practical solutions can help researchers identify theoretical opportunities as, for instance, when they can state a solution as a causal model. Consider a case of conceptual inference based on a process theory in which a set of design principles for sensemaking support systems (Seidel et al., 2018) involves digital data storage features for noticing and bracketing, an essential process in organizational sensemaking (Weick, 1995). Figure 4 visualizes the process of conceptual inference in the case of both variance theory and process theory and highlights how causal factors can provide a foundation to identify means. While, in the case of a variance theory, researchers attend to the independent variables that typically represent properties of entities (Burton-Jones, McLean, & Monod, 2014), in the case of process theory, prescriptive researchers use the elements of socio-technical process and typically focus on entities that participate in a process (Burton-Jones, McLean, & Monod, 2014) to identify how novel means such as instances of a new class of information systems may support (and perhaps alter) these elements.

In the case of conceptual inference, a justified theory's explanatory power and predictive accuracy serve as a foundation for identifying means that one expects to bring about a certain outcome (i.e., ends). Unjustified theories, despite their seemingly logical development and grounding, do not serve as a valid foundation for business decision-making because they are disconnected from empirical data, and their explanatory power and predictive accuracy remain unknown.

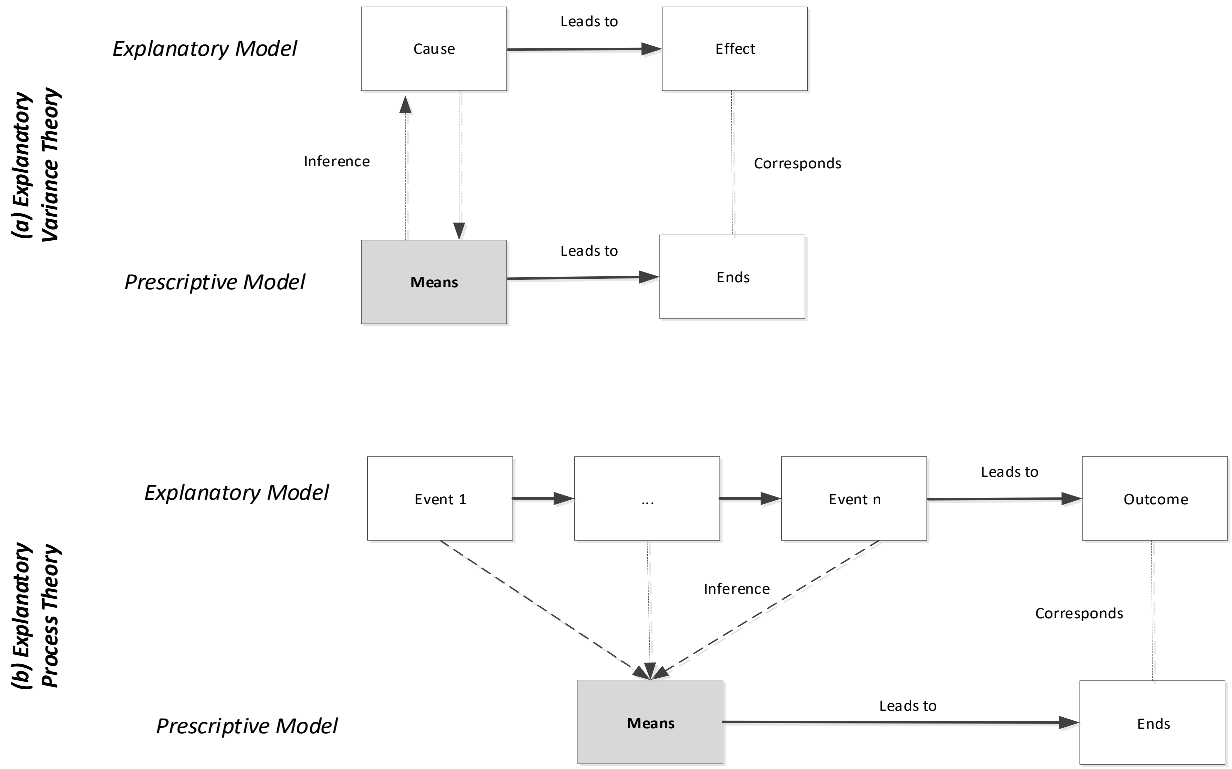

Figure 4. The Conceptual Inference Nexus in the Case of Variance Theory (Compare Goldkuhl, 2004; Kuechler & Vaishnavi, 2012) and Process Theory

To understand a theory, base an intervention on it and observe the results (Starbuck, 2004). Hence, if an action taken to address a specific cause succeeds, it indicates a theory's validity. If it does not achieve the anticipated result, either the explanatory model or the prescription lacked validity under the given boundary conditions. This perspective recognizes that researchers establish reality via studying real-world solutions (Rovelli, 2016, p. 3), and researchers should base their purposive design on causal inferencing.

As another form of integrating explanatory and predictive research practices and prescriptive research practices, researchers can introduce controllable variables into predictive models through **conceptual integration**, which, in turn, makes the model amenable for prescriptive research methods. A research stream on group support systems (GSSs), for instance, has experimentally tested various GSSs' features in the lab and field (e.g., Nunamaker, Hale, & Konsynski, 1987; Watson, DeSanctis, & Poole, 1988; Zigurs, Poole, & DeSanctis, 1988). In this case, system features (such as anonymous voting) directly represent prescriptions. Figure 5 visualizes this perspective.

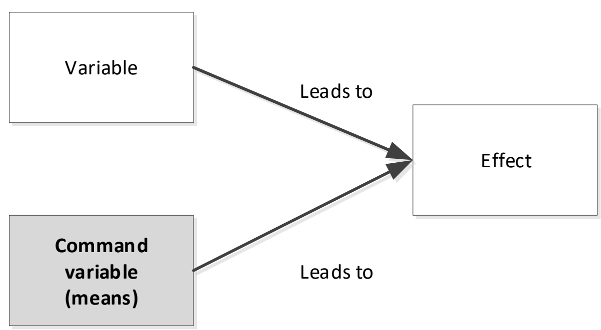

Figure 5. The Conceptual Integration Nexus: Controllable and Non-controllable Variables in the Same Model

Elaborating the nexuses between the two types of research transcends the dichotomy of the traditionalist view in which understanding precedes design and implementation and other positions such as Kurt Lewin's realization that intervention might precede understanding (Shneiderman, 2016). A failure of the two types of research to interact limits the potential of both. Intertwined, they represent the full panorama of scientific endeavor open to IS scholars.

Given humans' penchant for control (Beniger, 2009), a theory's social value depends on its ability to both describe the world and generate solutions to change it. Thus, knowledge gained from developing and testing solutions represents valuable input for increasing the alignment between theory and reality. The model we introduce highlights the intricate relationships and complementary nature of explanatory and predictive research on the one hand and prescriptive research on the other. In Section 4, we provide illustrative examples.

4 Illustrations

We use three examples that illustrate the interplay between the two types of research with different emphases on designing and implementing solutions. In the first study, researchers derived design principles (i.e., prescriptive statements) from existent theory on sensemaking (i.e., explanatory knowledge) and then tested and elaborated on them through implementing and testing a system through multiple cycles. The second study highlights how researchers based a solution on existent explanatory theory and, in turn, how reflecting on the solution contributed to explanatory theory. In the third study, researchers developed theory based on observing a solution in a practical setting. Table 7 summarizes the interrelationship between the two types of research in the three studies and highlights three key patterns of how explanatory and predictive research and prescriptive research interact synergistically.

Table 7. Patterns and Examples

Pattern	Description	Reference
Explanatory knowledge → prescriptive knowledge	Explanation precedes prescription	Seidel et al. (2018)
Explanatory knowledge ←→ prescriptive knowledge	Explanatory knowledge provides the basis for design and implementation, while an intervention's results can contribute to theory.	Lindgren et al. (2004)
Prescriptive knowledge → explanatory knowledge	Explanatory knowledge follows form design and implementation	Horton, Rogers, Pinsonneault, & McCormick (1992)

4.1 Example 1 (Seidel et al., 2018): Explanatory Knowledge → Prescriptive Knowledge

In their study on sensemaking support systems, Seidel et al. (2018) drew on previous sensemaking theory (Weick, 1995; Weick, Sutcliffe, & Obstfeld, 2005) to develop design principles for sensemaking support systems (**prescriptive knowledge**). They defined sensemaking support systems as "information systems that support organizational sensemaking activities" (p. 222). Here, sensemaking refers to the social process where organizational actors interpret the environment, construct meaning, and comprehend the world, which allows them to act (Maitlis & Christianson, 2014; Weick et al., 2005). The design principles are prescriptive statements in the form of means-ends relationships about how one should design this particular class of systems, such as "Provide features for interactive communication, so that the system affords users to engage in an open and inclusive discussion in environmental sustainability transformations" (Seidel et al., 2018, p. 227).

The researchers used these prescriptive statements as the foundation to design the architecture of an information system (**design**) that they implemented through a Web-based system and hosted in an organization (**implementation**) and then further developed as they went through three iterations to improve both the design and the underlying prescriptive statements (i.e., the design principles). Throughout the process, they made use of complementary theory. For instance, they used the theory of affordance (Gibson, 1977)—another explanatory theory—to formulate the design principles in terms of "provide features in order to afford action".

Thus, these authors used **conceptual inference** and **conceptual integration**. First, they used the theoretical work on sensemaking as an organizational process in order to derive what practices a sensemaking support system should support (conceptual inference). Second, they used these concepts to formulate prescriptive knowledge (conceptual integration). Thus, they illustrated how to translate explanatory theory (a process view of sensemaking) into prescription that they then used to design and implement a system to test and further develop that prescription. Tables 8 and 9 summarize the study. They show that the authors primarily operated in the prescriptive science space but that they grounded their prescriptions and associated intervention in existent theory.

Table 8. Example 1: Key Research Practices

<table>
<tr><th>Research practice</th><th>Description</th></tr>
<tr><td>Conceptualization</td><td>Developed initial design principles

Revised design principles (i.e., prescriptive knowledge) through multiple rounds of building and evaluating a system</td></tr>
<tr><td>Design</td><td>Design for a Web-based platform based on the design principles</td></tr>
<tr><td>Implementation</td><td>Implemented platform

Deployed platform in case organization</td></tr>
<tr><td>Observation</td><td rowspan="2">Collected data through 1) system-usage information and 2) focus groups with the goal to see whether the design principles (i.e., prescriptive statements), if implemented, would lead to the anticipated outcome (a sensemaking process to occur)</td></tr>
<tr><td>Description</td></tr>
</table>

Table 9. Example 1: Nexus Exploration

Nexus	Description
Conceptual nexus: conceptual inference	Used theory on sensemaking to identify how one should design systems that support sensemaking in organizations
Conceptual nexus: conceptual integration	Used concepts from theory on sensemaking to formulate design principles

Seidel et al. (2018) evaluated the suggested design principles in three rounds of implementing and evaluating this implementation. However, the findings and evaluation concern only one organization. The authors argued that, while they did not empirically show the design principles' prescriptive accuracy, they formulated them in such way that one could apply—and, hence, test—them in different contexts. Thus, they produced results with limited prescriptive accuracy, but repeated tests across context and time may show the proposed prescriptive statement' prescriptive accuracy.

4.2 Example 2 (Lindgren et al., 2004): The Interplay of Prescriptive and Explanatory Knowledge

Lindgren et al. (2004) used an action research study to develop design principles for competence management systems—systems specifically designed for managing organizational competencies in response to problems with existent systems that showed poor-quality competence data in database applications, spreadsheet, word documents, and so on. In accordance with guidelines for canonical action research (Susman & Evered, 1978), the authors went through two cycles of diagnosing, action planning, action taking, evaluating, and specifying learning. A structurational perspective on organizational competence that they grounded in previous literature on individual and organizational competence and Orlikowski's (1992) adaptation of Giddens' (1984) structuration theory (**theory**) informed their study. Specifically, their theoretical basis saw competence management systems as forming a part of the mediating structure that facilitates interaction between individual- and organizational-level competencies, and they argued that competence management systems must consider the reciprocal relationship between individual and organizational level competencies. That is, explanatory theory served as their logical point of departure.

They started the action research project by formulating a working proposition ("The problem of inaccurate and incomplete competence data can be resolved by using systems designed specifically for the purpose of managing organizational competencies, i.e., CMS" (Lindgren et al., 2004, p. 444)) that captured the essence of a means-end relationship. Based on this working proposition, they developed two design principles (**prescriptive knowledge**) (the principle of "balanced competence descriptions" and "the principle of user control"); that is, conceptualizations that added to the intended solution's overall elaboration. They translated the design principles into concrete solutions to guide the competence management system's configuration and implementation (**design and implementation**). They assessed the implementation in the participating organizations, analyzed the data they collected, and translated the findings into revised design principles, which, again, added to the suggested solution's overall elaboration. The first cycle revealed that they did not find support for the working proposition, and, thus, they developed a new one and new associated design principles to fashion a substantially different solution to the problem.

The study illustrates how prescriptive knowledge and explanatory knowledge interact. First, explanatory theory provided a logical point of departure to generate a prescription—an example of **conceptual inference**. As the researchers moved through two cycles of designing, implementing, observing, and re-conceptualizing, they deepened their understanding of organizational competence management (for instance, that "an infrastructure reflective of the job-based paradigm present problems for competence management in contemporary, knowledge-intensive organizations" (Lindgren et al., 2004, p. 468)). Thus, they capitalized on not only the **conceptualization nexus** but also the **observation and description nexuses**. Tables 10 and 11 summarize the study. They show that the authors primarily operated in the prescriptive space but that their analysis contributed to generating explanatory knowledge and, thus, understanding.

Table 10. Example 2: Key Research Practices

Research practice	Description
Design	Designed system to meet prescribed goals
Implementation	Deployed a previously designed and coded system
Observation	Assessed implementation in participating organizations
Description	
Conceptualization	Developed initial working proposition and design principles Revised working proposition and design principles
	Deepened knowledge of organizational competence management

Table 11. Example 2: Nexus Exploration

Nexus	Description
Conceptual nexus: conceptual inference	Identified design principles grounded in existent literature
Observation nexus	Reflecting on action research study that involved a solution based on prescriptions allowed the authors to more deeply understand organizational competence management
Description nexus	

4.3 Example 3 (Horton et al., 1992): Prescriptive Knowledge → Explanatory Knowledge

Few studies in which theorizing follows design and implementation in practical settings exist, which suggests IS scholars have an opportunity to discover novel theoretical insights by flipping the prevalent design science model where one bases design on explanatory and predictive theory. While practitioners care about the specific effect, scholars care about the generalizable nature of the outcome for similar IS manipulations.

Horton et al.'s (1992) study on the impact that face-to-face collaborative technology has on group writing demonstrates how **design and implementation** can provide an empirical basis for theorizing. They conducted an experiment in which they compared conventional and collaborative writing tools. Fittingly for an exploratory study, they used video recording, group-activity logging, questionnaires, and document assessment to record group behavior (**observation and description**). When theory does not drive a solution, researchers need a broad bandwidth approach to data capture so that they have sufficient diversity and viewing angles to develop a theoretical explanation. They noted that:

> *Our most significant discovery may be that groups used different patterned processes to complete the writing tasks in the two conditions. All of the groups planned, produced, and revised to some degree in both conditions. However, the amount of time spent on these activities, the amount of group versus individual work, and the patterns of tool use varied dramatically by condition.* (p. 34)

While these patterns were primarily descriptive, the authors applied conceptual labels to them and, thereby, took a step towards theorizing and identifying future research.

This example illustrates **observation**, **description**, and **conceptualization nexuses**. The authors generated observations by design and implementation and derived insights from multiple observational lenses and through conceptually describing key emergent patterns under technology use and non-use conditions. Their study demonstrates how one can—in an exploratory fashion—move from design and implementation to theoretical insight. Tables 12 and 13 summarize the study. They show that the authors moved from designing and implementing to contributing to understanding group interaction.

Table 12. Example 3: Key Research Practices

Research practice	Description
Design	Provided Capture Lab—a low-structure computerized meeting room—to support collaborative writing
Implementation	Experimental setting where one group uses the computer technology (Capture Lab) while another uses conventional writing tools
Observation	Video recording, group-activity logging, questionnaires, and document assessment to record group behavior
Description	
Conceptualization	The authors found that technology altered the group writing process and affected group interaction They conceptualized their findings through interaction patterns

Table 13. Example 3: Nexus Exploration

Nexus	Description
Observation nexus	Observations and succinct descriptions of design and implementation provided the foundation for explaining group interaction
Description nexus	
Conceptualization nexus	The authors used findings from observing design and implementation to conceptualize group interaction with and without computers

The authors established prescriptive accuracy through experimental testing. Of course, the typical limitations to external validity applied. If one used the system outside the laboratory, other factors that the authors might not have controlled for could impact the outcome from using the software. As such, we can see how, in order to establish prescriptive accuracy, researchers need to move beyond the laboratory setting; for instance, field experiments can provide a foundation to enhance an intervention's prescriptive accuracy.

All three cases highlight that limits to prescriptive accuracy exist and that the contextual nature of designing and implementing solutions can explain these limits. In Section 5, we discuss the limits to predictive and prescriptive accuracy.

5 The Limits to Predictive and Prescriptive Accuracy

Explanatory and predictive research and prescriptive research in IS range from investigating mere technical questions to, for instance, exploring the role that information systems play in the complex, socio-technical assemblages that characterize contemporary organizations. Some recent research has even moved beyond organizations to examine platform-based ecosystems (Parker, Van Alstyne, & Jiang, 2016). As a consequence, the degree to which we can accomplish predictive and prescriptive accuracy and what methods we can use depend on the specific socio-technical phenomenon we study. Specifically, the more complex the phenomenon under consideration, the more difficult it becomes to specify the boundary conditions under which explanatory and predictive knowledge and prescriptive knowledge apply.

Through the lens of the socio-technical systems model (Bostrom & Heinen, 1977a, 1977b) and its augmentation (O'Hara, Watson, & Kavan, 1999), which explicitly identifies types of change, we can comprehend these limits. The model suggests three orders of change: alpha, beta, and gamma. Alpha change occurs when technology modifies a task, beta change when technology revamps a person's role and associated tasks, and gamma change when organizations make coordinated alterations in technology, task, roles, and organizational structure. We extend the model to include delta change, which occurs when an ecosystem's perturbation creates ripples of change among its organizational members that can affect their structure, roles, tasks, or technology. We need this addition because the ecosystem represents possibly the most significant change in organizational form since the industrial revolution (Moore, 2006).

At its most simple form, alpha change involves a formal, deterministic system that changes a task (e.g., a more efficient algorithm). In the case when the alpha change impacts human tasks, one can often experimentally test it in the field or laboratory setting and, thereby, establish predictive and prescriptive accuracy. Researchers tested much GSS-related theory in a laboratory setting and have successfully incorporated some robust findings into practice as ThinkLets (Briggs, de Vreede, & Nunamaker, 2003; de Vreede, 2014) because they provide predictable improvements in a group's performance for certain tasks.

One cannot easily assess beta change due to the interplay between technology, roles, and tasks. People take time to learn new roles. One cannot easily discern beta change's effects because many variables other than technology and task affect a role, which makes predictive and prescriptive accuracy a more distant goal. Moreover, relationships between the technology, roles, and tasks can be reciprocal as over time technology shapes practice and vice versa (Leonardi, 2011; Orlikowski, 1992). That does not mean that researchers cannot anticipate a beta change's general direction but that there might be wide latitude and, thus, indeterminacy in the outcomes. Consequently, researchers study beta changes using different idiographic and nomothetic methods as it becomes necessary to "zoom in" in order to account for local idiosyncratic settings and "zoom out" in order to identify regularities across contexts and time.

Gamma change further challenges accuracy. One can observe but rarely manipulate structural change, and it occurs infrequently. Exogenous events often motivate gamma change, and they can continue unabated and inconsistently while organizational actors re-engineer a structure. Hence, researchers have little ability to distinguish between the effects of external forces and internal actions. Furthermore, gamma change might involve explanatory factors, such as industry, organizational maturity, technology stability, that one cannot assess based on one or a few cases. Gamma change sets an organization on a voyage of uncertainty, and neither research that focuses on explanation and prediction nor research that focuses on prescription can set the compass with any certainty. Gamma changes largely rely on informed action; that is, practitioners' tacit capability that, for instance, pattern matching that originates from prior case studies can inform (Flyvbjerg, 2001). Theories that focus on explaining rather than predicting how technology and social components interact can provide directional guidance (e.g., Leonardi, 2011; Orlikowski, 1992) but rarely predictive or prescriptive accuracy.

With the advent of software-based ecosystems (Gawer, 2011; Tiwana & Konsynski, 2010; Yoo, Boland, Lyytinen, & Majchrzak, 2012), we can also have delta change when a major disturbance disrupts a system of cooperating organizations. Its multiple participating hierarchies might each need to accommodate an internal gamma change. Delta- and gamma-level problems are the most complex problems that IS scholars address and the least amenable to prescriptive accuracy.

We can see that, as we move from largely deterministic systems such as algorithms that perform specific tasks to non-deterministic systems that involve various explanatory structural and individual factors, predictive and prescriptive accuracy decrease. Alpha changes enable one to isolate direct relationships between cause and effect. As we move to higher forms of change, the path between actions and outcomes becomes a tangle of other feasible explanatory factors (see Figure 6).

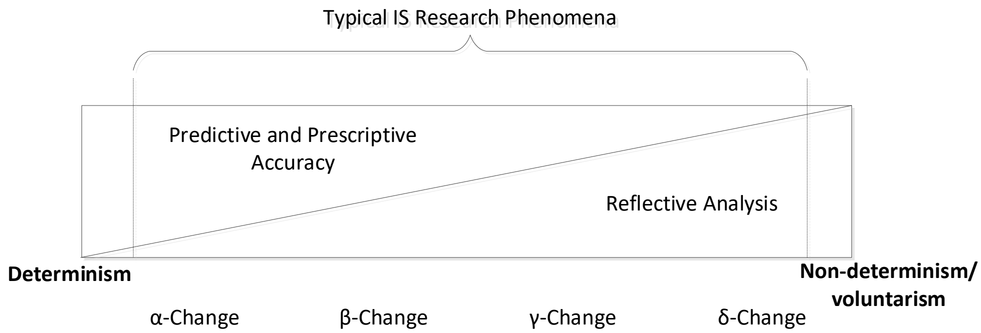

Figure 6. Predictive and Prescriptive Accuracy and Types of Socio-technical Change

Typical IS phenomena are neither purely deterministic nor purely voluntaristic without any regularity across contexts and across time. Despite the complexity, practitioners need to meet budgets and business goals such as sales targets to hit profit projections. Thus, while more complex non-deterministic settings are usually limited to rich, reflective analyses of cases and contexts at the level of description and conceptualization (Flyvbjerg, 2001; Schön, 1983), prediction and prescription are still desirable to the extent feasible. Studying practices might reveal "the great within the small" (Flyvbjerg, 2001, p. 134), and focusing on concrete cases does not prevent empirical generalizations (Flyvbjerg, 2001; Klein & Myers, 1999). Spaces for action exist outside particular human actors' minds and understanding, and, in complex social settings, we must not overemphasize individual agency at the cost of identifying regularities across contexts and across time (Bourdieu, 1977; Bourdieu & Wacquant, 1992).

6 Guidelines for Integrating Explanatory/Predictive and Prescriptive Research in IS

In this section, we derive guidelines that we ground in our analysis to help researchers conduct research that integrates the two modes of inquiry (see Table 14). We explain each guideline in turn.

Table 14. Guidelines for Integrating Explanatory/Predictive and Prescriptive Research in IS

	Guideline	Short description
1	Nexus exploration	When conducting explanatory and predictive research or prescriptive research, IS scholars should be sensitive toward identifying potential for research in both areas. They can identify such potential in stages such as observation, description, and conceptualization.
2	Conceptual integration clarity	Researchers should explicitly state when they translate explanatory and predictive statements into prescriptive statements and vice versa whenever possible (i.e., what concepts they integrated or what concepts provided the basis for their inferring new concepts).
3	Contextual fit	To allow researchers to translate explanations and predictions (through conceptual integration or conceptual inference) into prescriptions (and vice versa), contextual fit is prerequisite. There should not be a mismatch between the boundary conditions of the explanation and prediction context (i.e., what the theory explains and predicts) and the prescription context (i.e., where the prescription is deployed).
4	Predictive and prescriptive accuracy	Predictive and prescriptive accuracy represent equally legitimate research goals whose evaluation requires equal rigor and replication.
5	Practitioner-oriented communication	Prescriptive researchers need to translate their findings into a language that practitioners can easily access. In some situations, practitioners might be able to easily access prescriptive knowledge; however, in others, they will need to translate it. Researchers do not have to perform such translation in the same paper.

6.1 Guideline 1: Nexus Exploration

Due to reviewing norms and the predominant paradigms in our field, we often follow established research modes (Grover & Lyytinen, 2015). While every scientific method requires deep expertise and, thus, vindicates specialization, too narrow a focus might mean we miss research opportunities. If we succeed in meaningfully combining different research approaches (Rai, 2018), explanatory and predictive research and prescriptive research can mutually benefit. Particularly, as the explosive growth in information technology provides a multitude of explanatory and predictive research and prescriptive research opportunities for IS scholars. Researchers can use many of our research opportunities to pursue *both* justified explanations and predictions and justified prescriptions.

The same observation opportunity may yield explanatory, predictive, and prescriptive insight depending on researchers' perception lens. We suggest that researchers adopt a dual frame of reference that looks to elaborate or develop theory and examines intended effects efficacy. Does existing theory explain what happens?

A global company introduced an information system to achieve 100 percent electronic customer ordering (Smith & Watson, 2018). The new ordering system worked as intended. It had no technological flaws but experienced a poor adoption rate (20%). By applying systems thinking, Smith and Watson (2018) explained the low prescriptive accuracy and how to improve it. They also improved their theoretical understanding by gaining deeper insights into how key concepts interact. When observing the phenomenon, they looked for evidence (and counter-evidence) for the information system's efficacy and to theoretically explain the observed effects.

6.2 Guideline 2: Conceptual Integration Clarity

Engineering fields based on natural science, such as physics or chemistry, prominently focus on knowing explanatory principles and, thus, understanding underlying processes. While we cannot expect IS researchers to incessantly ground prescriptions to the same degree due to socio-technical phenomena's indeterministic and complex nature, explicating the conceptual relationships between explanatory and predictive knowledge on the one hand and prescriptive knowledge on the other (whenever possible) has important benefits. First, it adds rigor to the research process as it adheres to the same standards expected from theory building; prescriptive statements grounded in explanatory and predictive statements constitute justified statements, although the prescriptive accuracy still remains unknown. Second, it exploits the bi-directional relationship between explanatory and predictive knowledge and prescriptive knowledge. That is, if the design and implementation following the prescription produces a result that contradicts what an explanatory and predictive theory suggests, it can indicate that researchers need to revisit the underlying theory. Third, recognizing an underlying cause-effect relationship or underlying process allows researchers to explore various alternative solutions and, thus, various prescriptions since various potential solutions in any given situation exist (Pries-Heje & Baskerville, 2008).

6.3 Guideline 3: Contextual Fit

To allow researchers to translate explanations and predictions (through conceptual integration or conceptual inference) into prescriptions (and vice versa), contextual fit is prerequisite. There should not be a mismatch between the boundary conditions of the explanation and prediction context (i.e., what the theory explains and predicts) and the prescription context (i.e., where the prescription is deployed). Boundary conditions involve the temporal and contextual factors that define the limits for generalizability (Whetten, 1989), which is also relevant when one moves from explanation and prediction to prescription and vice versa. Can, for example, one apply an explanatory theory about big data analytics for providing services based on case studies in the insurance, banking, telecommunications, and e-commerce industries (Lehrer, Wieneke, vom Brocke, Jung, & Seidel, 2018) to develop prescriptions that remain valid in the manufacturing sector? If yes, what is the analytical rationale for this generalization?

6.4 Guideline 4: Predictive and Prescriptive Accuracy

Prescription ideally builds on a justified explanatory model. The need to justify and repeatedly evaluate a theory under varying boundary conditions becomes increasingly important (indeed, critical) as researchers derive prescriptive statements from that theory. In turn, researchers also need to rigorously test these prescriptive statements. To establish the predictive and prescriptive accuracy of knowledge about socio-technical systems, researchers need to clearly define the boundary conditions and provide an argument for their findings' generalizability (for a detailed discussion, see Lee & Baskerville, 2003; Tsang & Williams 2012).

As a field, we have been trained to justify and test theories' explanatory power and predictive accuracy, and a large theoretical body of explanatory and predictive knowledge that we can build on to develop prescriptions exists. In order to build an equally strong body of prescriptive knowledge, we need to recognize prescriptive accuracy as an equally legitimate research goal and accord prescriptive research equal status to that of justifying explanations and predictions. Unless researchers conduct repeated empirical assessments in various domains (Leik & Meeker, 1975, p. 3), they will lack the ability to establish boundary conditions, and a prescription's value will remain disputable and its effects' foundations mysterious. While the incentives to disqualify poor theories are weak (Starbuck, 2004), we need to follow medicine's and engineering's example and ensure that, when we identify poor practices, leading journals pay attention to them.

Prescriptive research must follow the same rigorous conceptualization, operationalization, and evaluation standards as explanatory and predictive research. There are clear guidelines to help researchers conduct, for example, experimental research (Gupta, Kannan, & Sanyal, 2018) and design science research (Gregor & Hevner, 2013; Peffers et al., 2007; Sein et al., 2011).

6.5 Guideline 5: Practitioner-oriented Communication

In developing justified prescriptions in IS, researchers focus on making practically useful contributions, and a key question concerns how practitioners can meaningfully capitalize on prescriptive knowledge (Lukyanenko & Parsons, forthcoming). One important challenge here concerns how researchers should communicate such applicable knowledge to practitioners (Te'eni, Seidel, & vom Brocke, 2017). On the one hand, researchers who embark on prescriptive research form part of a community of inquirers, use that community's lexicon, and, indeed, have to do so in order to engage with the discourse in a field. On the other hand, practitioners might find the language that researchers use difficult to access, which may render the contribution difficult to understand. We believe that the solution to this tension does not lie in departing from the lexicon that the community of inquiry uses when conducting the research. Instead, as the individuals who carry out explanatory and predictive research, prescriptive researchers need to translate their findings into a language that practitioners can easily access. There might be situations where prescriptive knowledge is easily accessible in its presented form, but in other situations such translation will be warranted. Clearly, it will often be easier to extract guidelines for practitioners from statements that are already in prescriptive form, compared to extracting implications from explanatory and predictive models, as is typically done in the implications section of a paper.

7 Conclusion

In this paper, we frame IS as both an explanatory and predictive science and a prescriptive science and describe how we can synergistically integrate the two through the explanation-prescription nexus. Prescriptive research cannot exist without rigorously developed theoretical foundations based on explanation and prediction, causality, and generalization. For a field to support the organizational and social change that information systems create, action must follow from explanations and predictions. We define the organizational impact of information systems in terms of predictive and prescriptive accuracy and describe the pathways of explanatory/predictive and prescriptive research and their interrelationships.

Positioning IS as having this dual role acknowledges that the field studies human-made systems; assumes that, in many situations, one should be able to explain and predict information systems' effects; and acknowledges that the field also aspires to improve these human-made systems' outcomes. We contend that the IS field requires this view in order to define, shape, and further develop its position as a leading scholarly field that studies the development, use, and impact of information systems in the digital age. We live in a world with complex problems that require various factors to design and implement effective systems and information systems in particular. As scholars skilled in systems thinking and deeply informed about the change agent of our time (i.e., information systems), we have a unique position to engage in creating innovations. This view concurs with a development that we can see across scholarly fields—a recent *Science* perspective on the global issue of creating a sustainable materials system highlighted how the scientific and engineering communities must collaborate to solve key problems associated with environmental degradation and pointed to the need for fundamental research *and* development (Olivetti & Cullen, 2018). The IS field needs to integrate explanatory and predictive research and prescriptive research to meet its social obligations.

With this work, we contribute to the ongoing debate about blending IS research traditions and respond to the call for cross-paradigm combinatorial research practices (Rai, 2018). Thus, we equip scholars with a framework that helps them position, conduct, and evaluate their research in relation to integrative, paradigm-spanning IS research. In this line of thinking, the framework we present:

1) Accommodates different methodological approaches that have explanation, prediction, and prescription as their primary orientation
2) Includes different types of theory in terms of purpose (e.g., explanation, prediction, prescription) and form (e.g., variance, process, and systems models)
3) Highlights the cyclic, iterative, and tentative nature of both explanatory/predictive and prescriptive research and their outcomes
4) Defines a metric for the output of explanatory and predictive research (predictive accuracy) and prescriptive accuracy (prescriptive accuracy)
5) Discusses the limits of accomplishing predictive and prescriptive accuracy when studying socio-technical systems
6) Describes explicit pathways for both types of research and how researchers can integrate them at the level of research practices, and
7) Avoids uncritically transferring concepts from other fields by recognizing the specific phenomena that the IS field studies, which range from information technology about which researchers can make deterministic statements to indeterminate, idiosyncratic, and socially disordered socio-technical assemblages.

While we would contend that the framework includes different methodological approaches, it still suggests that scientific inquiry concerns itself with discovering regularities across context and time and, thus, *abstract* conceptualizations—always on the basis that any such knowledge remains tentative and approximate (Dewey, 1938; Habermas, 2003). Thus, we acknowledge interpretation's role but always in light of moving towards conceptual understanding that can explain, predict, or prescribe. Still, we also acknowledge that researchers cannot easily accomplish these goals when studying complex situations that involve human agency. We argue that we should seek explanatory power, predictive accuracy, and prescriptive accuracy whenever possible and subject such findings to continuous testing and justification.

References

Aliseda, A. (2006). *Abductive reasoning* (vol. 330). Berlin: Springer.

Arnott, D., & Pervan, G. (2005). A critical analysis of decision support systems research. *Journal of Information Technology*, *20*(2), 67-87.

Arnott, D., & Pervan, G. (2012). Design science in decision support systems research: An assessment using the Hevner, March, Park, and Ram guidelines. *Journal of the Association for Information Systems*, *13*(11), 923-949.

Arnott, D., & Pervan, G. (2014). A critical analysis of decision support systems research revisited: The rise of design science. *Journal of Information Technology*, *29*(4), 269-293.

Arthur, W. B. (2009). *The nature of technology: What it is and how it evolves.* New York, NY: Simon and Schuster.

Bailey, J. R., & Eastman, W. N. (1996). Tensions between science and service in organizational scholarship. *The Journal of Applied Behavioral Science*, *32*(4), 350-355.

Baskerville, R. (1999). Investigating information systems with action research. *Communications of the Association for Information Systems*, *2*, 1-32.

Baskerville, R., & Wood-Harper, A. T. (1998). Diversity in information systems action research methods. *European Journal of Information Systems*, *7*(2), 90-107.

Beniger, J. (2009). *The control revolution: Technological and economic origins of the information society.* Boston, MA: Harvard University Press.

Berente, N., Seidel, S., & Safadi, H. (2018). Data-driven computationally-intensive theory development. *Information Systems Research*, *30*(1), 50-64.

Bichler, M., Frank, U., Avison, D., Malaurent, J., Fettke, P., Hovorka, D., Kramer, J., Schnurr, D., Muller, B., Suhl, L., & Thalheim, B. (2016). Theories in business and information systems engineering. *Business & Information Systems Engineering*, *58*(4), 291-319.

Bostrom, R. P., & Heinen, J. S. (1977a). MIS problems and failures: A socio-technical perspective (part I: The causes). *MIS Quarterly*, *1*(3), 17-32.

Bostrom, R. P., & Heinen, J. S. (1977b). MIS problems and failures: A socio-technical perspective (part II: The application of socio-technical theory). *MIS Quarterly*, *1*(4), 11-28.

Bourdieu, P. (1977). *Outline of a theory of practice* (vol. 16). Cambridge, UK: Cambridge University Press.

Bourdieu, P., & Wacquant, L. J. (1992). *An invitation to reflexive sociology*. Chicago, IL: University of Chicago Press.

Briggs, R. O., De Vreede, G.-J., & Nunamaker, J. F., Jr. (2003). Collaboration engineering with thinklets to pursue sustained success with group support systems. *Journal of Management Information Systems*, *19*(4), 31-64.

Bunge, M. (1967). *Scientific research I: The search for system*. New York, NY: Springer Verlag.

Burton-Jones, A., McLean, E. R., & Monod, E. (2014). Theoretical perspectives in IS research: From variance and process to conceptual latitude and conceptual fit. *European Journal of Information Systems*, *24*(6), 664-679.

Chatman, J. A., & Flynn, F. J. (2005). Full-cycle micro-organizational behavior research. *Organization Science*, *16*(4), 434-447.

Churchman, C. W. (1971). *The design of inquiring systems: Basic concepts of systems and organization*. New York, NY: Basic Books.

de Vreede, G.-J. (2014). Two case studies of achieving repeatable team performance through collaboration engineering. *MIS Quarterly Executive*, *13*(2), 115-129.

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research*, *3*(1), 60-95.

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of MIS*, *19*(4), 9-30.

Dewey, J. (1938). *Logic: The theory of Inquiry*. New York, NY: Henry Holt.

Dubin, R. (1969). *Theory building*. New York, NY: The Free Press.

Flyvbjerg, B. (2001). *Making social science matter: Why social inquiry fails and how it can succeed again.* Cambridge, UK: Cambridge University Press.

Ford, E. W., Duncan, W. J., Bedeian, A. G., Ginter, P. M., Rousculp, M. D., & Adams, A. M. (2003). Mitigating risks, visible hands, inevitable disasters, and soft variables: Management research that matters to managers. *The Academy of Management Executive*, *17*(1), 46-60.

Gamma, E. (1995). *Design patterns: Elements of reusable object-oriented software*. New York, NY: Pearson.

Gawer, A. (2011). *Platforms, markets and innovation.* Northampton, MA: Edward Elgar Publishing.

Gero, J. S. (1990). Design prototypes: A knowledge representation schema for design. *AI Magazine*, *11*(4), 26-36.

Giboney, J. S., Briggs, R. O., & Nunamaker, J. F., Jr. (2016). Special issue: Designing tools to answer great information systems research questions. *Journal of Management Information Systems, 33*(4), 938-941.

Gibson, J. J. (1977). The theory of affordances. In R. Shaw & J. Bransford (Eds.), *Perceiving, acting and knowing: Toward an ecological psychology* (pp. 67-82). Hillsdale, NJ: Lawrence Erlbaum Associates.

Giddens, A. (1984). *The constitution of society: Outline of the theory of structuration*. Berkeley, CA: University of California Press.

Glaser, B. G., & Strauss, A. L. (1967). *The discovery of grounded theory: Strategies for qualitative research*. Chicago, IL: Aldine Publishing Company.

Goes, P. B. (2014). Editor's comments: Design science research in top information systems journals. *MIS Quarterly*, *38*(1), iii-viii.

Goldkuhl, G. (2004). Design theories in information systems—a need for multi-grounding. *Journal of Information Technology Theory and Application*, *6*(2), 59-72.

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

Gregor, S., Chandra Kruse, L., & Seidel, S. (Forthcoming). The anatomy of a design principles. *Journal of the Association for Information Systems.*

Gregor, S., & Hevner, A. R. (2013). Positioning and presenting design science research for maximum impact. *MIS Quarterly*, *37*(2), 337-355.

Gregor, S., & Hovorka, D. S. (2011). Causality: The elephant in the room in information systems epistemology. In *Proceedings of the 19th European Conference on Information Systems*.

Gregor, S., & Jones, D. (2007). The anatomy of a design theory. *Journal of the Association for Information Systems*, *8*(5), 313-335.

Gregor, S., Müller, O., & Seidel, S. (2013). Reflection, abstraction, and theorizing in design and development research. In *Proceedings of the 21st European Conference on Information Systems.*

Grover, V., & Lyytinen, K. (2015). New State of play in information systems research: The push to the edges. *MIS Quarterly*, *39*(2), 271-296.

Gupta, A. (2017). Editorial thoughts: What and how ISR publishes. *Information Systems Research*, *28*(1), 1-4.

Gupta, A., Kannan, K., & Sanyal, P. J. (2018). Economic experiments in information systems. *MIS Quarterly*, *42*(2), 595-606.

Habermas, J. (2003). *Truth and justification*. Cambridge, MA: MIT Press.

Handfield, R., & Melnyk, S. A. (1998). The scientific theory-building process: A primer using the case of TQM. *Journal of Operations Management*, *16*(4), 321-339.

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, *28*(1), 75-105.

Hibbeln, M., Jenkins, J., Schneider, C., Valacich, J., & Weinmann, M. (2017). How is your user feeling? Inferring negative emotions from mouse cursor movements. *MIS Quarterly*, *41*(1), 1-21.

Hirschheim, R., Klein, H. K., & Lyytinen, K. (1995). *Information systems development and data modeling: conceptual and philosophical foundations*. Cambridge, UK: Cambridge University Press.

Horton, M., Rogers, P., Pinsonneault, A., & McCormick, M. (1992). Exploring the impact of face-to-face collaborative technology on group writing. *Journal of Management Information Systems*, *8*(3), 27-48.

Jenkins, J. L., Anderson, B. B., Vance, A., Kirwan, C. B., & Eargle, D. J. I. S. R. (2016). More harm than good? How messages that interrupt can make us vulnerable. *Information Systems Research*, *27*(4), 880-896.

Keen, P. G. W. (1980). MIS research: Reference disciplines and a cumulative tradition. In *Proceedings of the International Conference on Information Systems.*

Keen, P. G. W. (1981). Value analysis: Justifying decision support systems. *MIS Quarterly*, *5*(1), 1-15.

Klein, H. K., & Myers, M. D. (1999). A set of principles for conducting and evaluating interpretive field studies in information systems. *MIS Quarterly*, *23*(1), 67-93.

Kuechler, W., & Vaishnavi, V. (2012). A framework for theory development in design science research: Multiple perspectives. *Journal of the Association for Information Systems*, *13*(6), 395-423.

Lawrence, P. R. (1992). The challenge of problem-oriented research. *Journal of Management Inquiry*, *1*(2), 139-142.

Lee, A. S., & Baskerville, R. L. (2003). Generalizing generalizability in information systems research. *Information Systems Research*, *14*(3), 221-243.

Lehrer, C., Wieneke, A., vom Brocke, J., Jung, R., & Seidel, S. (2018). How big data analytics enables service innovation: Materiality, affordance, and the individualization of service. *Journal of Management Information Systems, 35*(2), 424-460.

Leik, R. K., & Meeker, B. F. (1975). *Mathematical sociology*. New York, NY: Prentice Hall.

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly*, *35*(1), 147-168.

Leonardi, P. M. (2012). Materiality, sociomateriality, and socio-technical systems: What do these terms mean? How are they related? Do we need them? In P. M. Leonardi, B. A. Nardi, & J. Kallinikos (Eds.), *Materiality and organizing: Social interaction in a technological world* (pp. 25-48). Oxford, UK: Oxford University Press.

Lin, Y.-K., Chen, H., Brown, R. A., Li, S.-H., & Yang, H.-J. J. M. Q. (2017). Healthcare predictive analytics for risk profiling in chronic Care: A Bayesian multitask learning approach. *MIS Quarterly*, *41*(2), 473-495.

Lindgren, R., Henfridsson, O., & Schultze, U. (2004). Design principles for competence management systems: A synthesis of an action research study. *MIS Quarterly*, *28*(3), 435-472.

Lukyanenko, R., & Parsons, J. (forthcoming). Design theory indeterminacy: What is it, how can it be reduced, and why did the polar bear drown? *Journal of the Association for Information Systems*.

Maitlis, S., & Christianson, M. (2014). Sensemaking in organizations: Taking stock and moving forward. *Academy of Management Annals*, *8*(1), 57-125.

March, T. S., & Smith, G. (1995). Design and natural science research on information technology. *Decision Support Systems*, *15*(4), 251-266.

Markus, M. L., & Silver, M. S. (2008). A foundation for the study of IT effects: A new look at DeSanctis and Poole's concepts of structural features and spirit. *Journal of the Association for Information Systems*, *9*(10), 609-632.

Markus, M. L., & Robey D. (1988). Information technology and organizational change: Causal structure in theory and research. *Management Science*, *34*(5), 583-598.

Moore, J. F. (2006). Business ecosystems and the view from the firm. *Antitrust Bulletin*, *51*, 31-75.

Müller-Wienbergen, F., Müller, O., Seidel, S., & Becker, J. (2011). Leaving the beaten tracks in creative work - A design theory for systems that support convergent and divergent thinking. *Journal of the Association for Information Systems*, *12*(11), 714-740.

Mumford, E., Hirschheim, R., Fitzgerald, G., & Wood-Harper, A. (1985). *Research methods in information systems.* Amsterdam: North-Holland Publishing Co.

Myers, M. D. (1999). Investigating information systems with ethnographic research. *Communications of the Association for Information Systems*, *2*, 1-20.

Niiniluoto, I. (1993). The aim and structure of applied research. *Erkenntnis*, *38*, 1-21.

Nunamaker, J. F., Jr., Chen, M., & Purdin, T. D. (1990). Systems development in information systems research. *Journal of Management Information Systems*, *7*(3), 89-106.

Nunamaker, J. F., Jr., Hale, J., & Konsynski, B. R. (1987). Facilitating group creativity: Experience with a group decision support system. *Journal of Management Information Systems*, *3*(4), 6-19.

Nunamaker, J. F., Jr., Twyman, N. W., Giboney, J. S., & Briggs, R. O. (2017). Creating high-value real-world impact through systematic programs of research. *MIS Quarterly*, *41*(2), 335-351.

O'Hara, M. T., Watson, R. T., & Kavan, C. B. (1999). Managing the three levels of change. In*formation Systems Management Journal*, *16*(3), 63-70.

Olivetti, E. A., & Cullen, J. M. (2018). Toward a sustainable materials system. *Science*, *360*(6396), 1396-1398.

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science*, *3*(3), 398-427.

Orlikowski, W. J. (1993). CASE tools as organizational change: Investigating incremental and radical changes in systems development. *MIS Quarterly*, *17*(3), 309-340.

Parker, G., Van Alstyne, M., & Jiang, X. (2016). *Platform ecosystems: How developers invert the firm.* Retrieved from http://ide.mit.edu/sites/default/files/publications/Platform%20Ecosystems-%20How%20Developers%20Invert%20the%20Frim.pdf

Pearl, J. (2018). The seven tools of causal inference, with reflections on machine learning. *Communications of the ACM*, *62*(3), 54-60.

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, *24*(3), 45-77.

Peirce, C. S. (1955). The scientific attitude and fallibilism. In J. Buchler (Ed.), *Philosophical writings of Peirce* (pp. 42-59). New York, NY: Dover

Peirce, C. S. (1997). *Pragmatism as a principle and method of right thinking: The 1903 Harvard lectures on pragmatism*. New York, NY: SUNY Press.

Pentland, B. T. (1999). Building process theory with narrative: From description to explanation. Ac*ademy of Management Review*, *24*(4), 711-724.

Pfeffer, J., & Fong, C. T. (2002). The end of business schools? Less success than meets the eye. *Academy of Management Learning & Education*, *1*(1), 78-95.

Piccoli, G. (2012). *Information systems for managers: Texts & cases*. Hoboken, NJ: John Wiley & Sons.

Popper, K. R. (2002). *The logic of scientific discovery*. London, UK: Routledge.

Power, D. J. (2007). *A brief history of decision support systems.* Retrieved from https://dssresources.com/history/dsshistory.html

Pressman, R. S. (2005). *Software engineering: A practitioner's approach.* New York, NY: Palgrave Macmillan.

Pries-Heje, J., & Baskerville, R. (2008). The design theory nexus. *MIS Quarterly*, *32*(4), 731-755.

Rai, A. (2017). Editor's comments: Avoiding type III errors: Formulating IS research problems that matter. *MIS Quarterly*, *41*(2), iii-vii.

Rai, A. (2018). Editor's comments: Beyond outdated labels: The blending of IS research traditions. *MIS Quarterly*, *42*(1), iii-vi.

Rai, A., Burton-Jones, A., Chen, H., Gupta, A., Hevner, A. R., Ketter, W., Parsons, J., Rao, H. R., Sarker, S., & Yoo, Y. (2017). Diversity of design science research. *MIS Quarterly*, 41(1), iii-xviii.

Recker, J. (2013). *Scientific research in information systems: A beginner's guide*. Berlin: Springer.

Reynolds, P. D. (1971). *A primer in theory construction*. Needham Heights, MA: Allyn and Bacon.

Rosemann, M., & Vessey, I. (2008). Toward improving the relevance of information systems research to practice: The role of applicability checks. *MIS Quarterly*, *32*(1), 1-22.

Rovelli, C. (2016). *Seven brief lessons on physics*. New York, NY: Riverhead Books.

Schön, D. A. (1983). *The reflective practitioner: How professionals think in action.* New York, NY: Routledge.

Scott, S. V., & Orlikowski, W. J. (2012). Reconfiguring relations of accountability: Materialization of social media in the travel sector. *Accounting, Organizations and Society*, *37*(1), 26-40.

Seidel, S., Chandra Kruse, L., Szekely, N., Gau, M., & Stieger, D. (2018). Design principles for sensemaking support systems in environmental sustainability transformations. *European Journal of* In*formation Systems*, *27*(2), 221-247.

Sein, M. K., Henfridsson, O., Purao, S., Rossi, M., & Lindgren, R. (2011). Action design research. *MIS Quarterly*, *35*(1), 37-56.

Shmueli, G. (2010). To explain or to predict? *Statistical Science*, *25*(3), 289-310.

Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. *MIS Quarterly*, *35*(3), 553-572.

Shneiderman, B. (2016). *The new ABCs of research: Achieving breakthrough collaborations*. Oxford, UK: Oxford University Press.

Simon, H. A. (1990). Prediction and prescription in systems modeling. *Operations Research*, *38*(1), 7-14.

Simon, H. A. (1996). *The sciences of the artificial*. Cambridge, MA: MIT Press.

Singleton, J. P., & Straits, B. C. (2010). *Approaches to social research*. Oxford, UK: Oxford University Press.

Singleton, J. P., McLean, E. R., & Altman, E. N. (1988). Measuring information systems performance: Experience with the management by results system at Security Pacific Bank. *MIS Quarterly*, *12*(2), 325-337.

Smith, H. A., & Watson, R. T. (2018). Digital transformation at Carestream Health. *MIS Quarterly Executive*, *18*(1), 85-98.

Snow, C. P. (1959). *The two cultures and the scientific revolution. Cambridge*, UK: Cambridge University Press.

Starbuck, W. H. (2004). Vita contemplativa: Why I stopped trying to understand the real world. Or*ganization Studies*, *25*(7), 1233-1254.

Stokes, D. E. (1997). *Pasteur's quadrant: Basic science and technological innovation*. Washington, DC: Brookings Institution Press.

Susman, G. I., & Evered, R. D. (1978). An assessment of the scientific merits of action research. *Administrative Science Quarterly*, *23*(4), 582-603.

Te'eni, D., Seidel, S., & vom Brocke, J. (2017). Stimulating dialog between information systems research and practice. *European Journal of Information Systems*, *26*(6), 541-545

Tiwana, A., & Konsynski, B. (2010). Complementarities between organizational IT architecture and governance structure. *Information Systems Research*, *21*(2), 288-304.

Tsang, E. W. K., & Williams, J. N. (2012) Generalization and induction: Misconceptions, clarifications, and a classification of induction. *MIS Quarterly*, *36*(3), 729-748.

Van de Ven, A. H. (2007). *Engaged scholarship: A guide for organizational and social research*. Oxford, UK: Oxford University Press.

Venable, J., Pries-Heje, J., & Baskerville, R. (2016). FEDS: A framework for evaluation in design science research. *European Journal of Information Systems*, *25*(1), 77-89.

Vogel, D. R., & Wetherbe, J. C. (1984). MIS research: A profile of leading journals and universities. *The DATABASE for Advances in Information Systems*, *16*(1), 3-14.

Von Wright, G. H. (2004). *Explanation and understanding*. New York, NY: Cornell University Press.

Walls, J. G., Widmeyer, G. R., & El Sawy, O. A. (1992). Building an information system design theory for vigilant EIS. *Information Systems Research*, *3*(1), 36-59.

Walls, J. G., Widmeyer, G. R., & El Sawy, O. A. (2004). Assessing information system design theory in perspective: How useful was our 1992 initial rendition? *Journal of Information Technology Theory and Application*, *6*(2), 43-58.

Walsham, G. (2012). Are we making a better world with ICTs: Reflections on a future agenda for the IS field. *Journal of Information Technology*, *27*(2), 87-93.

Watson, R. T. (2014). A personal perspective on a conceptual foundation for information systems. *Journal of the Association for Information Systems*, *15*(8), 514-535.

Watson, R. T., DeSanctis, G., & Poole, M. S. (1988). Using a GDSS to facilitate group consensus: Some intended and unintended consequences. M*IS Quarterly*, *12*(3), 463-478.

Watson, R. T., Pitt, L. F., & Kavan, C. B. (1998). Measuring information systems service quality: Lessons from two longitudinal case studies*. MIS Quarterly*, *22*(1), 61-79.

Weick, K. E. (1989). Theory construction as disciplined imagination. *Academy of Management Review*, *14*(4), 516-531.

Weick, K. E. (1995). *Sensemaking in organizations* (vol. 3). Thousand Oaks, CA: Sage.

Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the process of sensemaking. O*rganization Science*, *16*(4), 409-421.

Whetten, D. A. (1989). What constitutes a theoretical contribution? *Academy of Management Review*, *14*(4), 490-495.

Yoo, Y., Boland, R. J., Jr., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science*, *23*(5), 1398-1408.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, *21*(4), 724-735.

Zigurs, I., Poole, M. S., & DeSanctis, G. L. (1988). A study of influence in computer-mediated group decision making. *MIS Quarterly*, *12*(4), 625-644.

About the Authors

Stefan Seidel is Professor and Chair of Information Systems and Innovation at the Institute of Information Systems at the University of Liechtenstein and currently holds an Honorary Professorship of Business Information Systems at the National University of Ireland, Galway. His research focuses on digital innovation and transformation in organizations and society. Stefan's work has been published in leading journals, including *MIS Quarterly*, *Information Systems Research*, *Journal of Management Information Systems*, *Journal of the Association for Information Systems*, *Journal of Information Technology*, *European Journal of Information Systems*, *Communications of the ACM*, *IEEE Computer*, and several others. He is an Associate Editor for *MIS Quarterly*.

Richard T. Watson is a Regents Professor and the J. Rex Fuqua Distinguished Chair for Internet Strategy in the Terry College of Business at the University of Georgia. He is a former President of the Association for Information Systems. In 2011, he received the Association for Information Systems' LEO award, which is given for exceptional lifetime achievement in Information Systems. The Liechtenstein Consortium for Digital Capital Creation has been founded based on the ideas in his book, *Capital, Systems, and Objects*. For about a decade, he was Research Director for the Advanced Practices Council of the Society of Information Management and a visiting researcher at the Research Institute of Sweden (RISE) Viktoria in Gothenburg. He is a currently a senior visiting professor at the Southern University of Science and Technology (SUSTech) in Shenzhen, China.