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SPECIAL ISSUE: COMPLEXITY & IS RESEARCH

COMPLEXITY AND INFORMATION SYSTEMS RESEARCH IN THE EMERGING DIGITAL WORLD[1]

Hind Benbya
Technology and Innovation Management, Montpellier Business School, 2300 Avenue des Moulins,
Montpellier 34185 Cedex 4, FRANCE {h.benbya@montpellier-bs.com}

Ning Nan
Sauder School of Business, University of British Columbia, 2053 Main Mall,
Vancouver V6T 1Z2 British Columbia, CANADA {ning.nan@sauder.ubc.ca}

Hüseyin Tanriverdi
McCombs School of Business, The University of Texas at Austin
Austin, TX 78712 U.S.A. {Huseyin.Tanriverdi@mccombs.utexas.edu}

Youngjin Yoo
Department of Design & Innovation, The Weatherhead School of Management, Case Western
Reserve University, 10900 Euclid Avenue, Cleveland, Ohio 44106-7235 U.S.A. and
Warwick Business School, University of Warwick, Coventry CV4 7RL UNITED KINGDOM {yxy23@case.edu}

Complexity is all around us in this increasingly digital world. Global digital infrastructure, social media, Internet of Things, robotic process automation, digital business platforms, algorithmic decision making, and other digitally enabled networks and ecosystems fuel complexity by fostering hyper-connections and mutual dependencies among human actors, technical artifacts, processes, organizations, and institutions. Complexity affects human agencies and experiences in all dimensions. Individuals and organizations turn to digitally enabled solutions to cope with the wicked problems arising out of digitalization. In the digital world, complexity and digital solutions present new opportunities and challenges for information systems (IS) research. The purpose of this special issue is to foster the development of new IS theories on the causes, dynamics, and consequences of complexity in increasing digital sociotechnical systems. In this essay, we discuss the key theories and methods of complexity science, and illustrate emerging new IS research challenges and opportunities in complex sociotechnical systems. We also provide an overview of the five articles included in the special issue. These articles illustrate how IS researchers build on theories and methods from complexity science to study wicked problems in the emerging digital world. They also illustrate how IS researchers leverage the uniqueness of the IS context to generate new insights to contribute back to complexity science.

Keywords: Complexity, sociotechnical systems, emergence, coevolution, chaos, scalable dynamics digitalization

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Introduction

When we conduct a search on Google, it returns hundreds, of thousands, results instantaneously. The results not only reflect the interests of the one who is doing the search, but also the millions of internet users who created or clicked on hyperlinks of websites. As more users search, link, and click with similar keywords, the results will continue to change according to user location and search time. A search for "Korean restaurants" in Munich, Germany, for example, gives different results from a search in Cleveland, OH, USA. Conducting the same search a day or two later also produces different results. A simple Google search result is an emergent property, a complex web of interactions among users, websites, topics, advertisers, and many other social or technical entities. In short, our daily experience of using mundane digital tools is a dynamic emergent outcome of complex sociotechnical systems.

As early as 2010, the world-wide production of transistors has exceeded that of rice, and is much cheaper (Lucas et al. 2012). Devices—large and small—powered by microprocessors and connected by the internet are filling every inhabited corner of the earth. Some of these devices are not just passively waiting for commands; equipped with a powerful artificial intelligence engine, they often act on their own. We already see autonomous vehicles on the streets interacting with traffic signals that respond to changing traffic patterns, in the midst of human-controlled vehicles and pedestrians. Sprinklers are connected to the weather service on the internet to control the amount of water on a lawn. The temperature of millions of houses is controlled by Nest connected to the Google Home Assist service. Connected speakers recommend different music playlists based on the time, location, and, of course, your preference. Social network services also enable every user as a potential content creator on the internet. Once created, user-generated content can be liked, shared, and mashed with other content by other users, often creating unpredictably complex forms of diffusions. Digital platform ecosystems such as Uber and AirBnB connect millions of users and providers globally. More than 80% of movies watched on Netflix are recommended by algorithms.[2]

These examples illustrate truly astonishing advances from the humble start of computers in organizations in the early 20th century. After merely a few decades, what once seemed to be glorified calculators have evolved into digital technologies that permeate our lives and work. These digital technologies in turn foster new sociotechnical systems such as wikis, social media, and platform ecosystems that are fundamentally changing the way people work and live.

Not every technological invention has such a transformational impact. What set apart digital technologies? At the heart of digital technologies is symbol-based computation. Bistrings (0s and 1s) provide a standard form of symbols to encode input, process, and output of a wide variety of tasks (Faulkner and Runde 2019). They reduce the design specificity of hardware for operationalizing the symbol-based computation. Furthermore, simplicity of bitstrings eases the effort to shrink the size, reduce the cost, and increase the processing power of hardware. Symbol-based computation provides a generalizable and applicable mechanism to unite the operations of matter and the abstract mental processes (Lovelace 1842). It lays the foundation for digital technology to rapidly advance beyond the function of a calculator. More importantly, symbol-based computation sets in motion the emergence of complex sociotechnical systems.

Emanating from symbol-based computation are a few complexity-inducing characteristics of digital technologies.

- Embedded: as described by the vision for symbol-based computation (Lovelace 1842; Shannon 1993, Turning 1950), digital capabilities are increasingly embedded in objects that previously have pure material composition (Yoo et al. 2012). Digital capabilities can encode and automate abstract cognitive processes for converting new information into adaptive changes of objects. They also enable objects to provide decision support to adaptive cognitive processes of social actors.

- Connected: objects embedded with digital capabilities and users of such objects can be connected into webs of sociotechnical relations (Sarker et al. 2019) because symbol-based computation homogenizes data (Yoo 2010). When information is shared in the webs of sociotechnical relations, abstract cognitive processes encoded in objects or possessed by social actors become mutually dependent.

- Editable: digital technologies are editable (Kallinikos et al. 2013; Yoo 2012) due to symbol-based computation. This editability allows increasingly diverse cognitive processes to be introduced into the webs of sociotechnical relations. Recurrent adaptation of diverse, connected, and mutually dependent objects and social actors can amplify or diminish an initial change in a sociotechnical system, producing outcomes that defy simple extrapolation from the initial change (Arthur 2015; Holland 1995; Page 2010). Complexity, therefore, becomes a salient attribute of sociotechnical systems.

[2] See https://mobilesyrup.com/2017/08/22/80-percent-netflix-shows-discovered-recommendation/.

- Reprogrammable: through the separation of hardware and software of symbol-based computation, digital technology is reprogrammable (Yoo et al. 2010). The same hardware can perform different functions depending on the software that runs on the device.

- Communicable: digital technologies are communicable by following a set of agreed-upon protocols (Lyytinen and King, 2006; Yoo 2010). With the pervasive diffusion of digital technologies, they now form a global digital infrastructure (Tilson et al. 2010).

- Identifiable: each and every device connected to the digital infrastructure is uniquely identifiable through its own unique address (Yoo 2010). The increasing digital penetration leads to a higher degree of identifiability, allowing for more granular manipulation levels of digital objects.

- Associable: digital objects are associable through shared traits. The associability of distributed heterogeneous devices and data allows one to identify emerging patterns across different realms and geographies in a way that was simply not possible in the past.

Digital technologies not only give rise to complex sociotechnical systems; they also distinguish sociotechnical systems from other complex physical or social systems. While complexity in physical or social system is predominantly driven by either material operations or human agency, complexity in sociotechnical systems arises from the continuing and evolving entanglement of the social (human agency), the symbolic (symbol-based computation in digital technologies), and the material (physical artifacts that house or interact with computing machines). The functions of digital technologies and the roles of social actors are perpetually defined and redefined by each other (Faulkner and Runde 2019; Zittrain 2006). This sociotechnical entanglement limits the generalizability of complexity insights obtained from nondigital systems to complex digital systems. Furthermore, while material operations or human agency either increase or dampen complexity in physical or social systems, digital technologies can both mitigate and intensify complexity. This is because individuals and organizations engaged with complex sociotechnical systems often turn to digital technologies (e.g., data analytics) for solutions to complex problems. Yet, the application of a solution can instigate a new round of digitally enabled interactions that diminish the intended effect of the solution. This dual effect of digital technologies on complexity can produce dynamic interaction patterns and outcomes that are qualitatively different from those in other complex systems.

The distinct effects of digital technologies on complex sociotechnical systems present an important opportunity for information systems (IS) researchers to extract novel insights regarding the nature and relevance of digital technologies. IS researchers can apply theories and methods from complexity science to model observations that defy simple extrapolation from initial changes in a sociotechnical system. In this essay, we introduce key complexity theories such as emergence, coevolution, chaos, and scalable dynamics as the most likely foundation for IS researchers to rethink predictability, causality, boundary, and durability of observations in the digital world. Subsequently, we explain how the centrality of symbol-based computation in IS research paves the way for IS-specific research themes to extend complexity science. The articles in this special issue are briefly described to illustrate a few prominent themes such as IS development for rapidly changing requirements and using digital technologies to steer or tame complexity.

Complexity Science: Key Theories and Methods

Complexity science's origins lie in 50 years of research into nonlinear dynamics in natural sciences and spans a variety of scholarly disciplines including biology (Kauffman 1993), chemistry (Prigogine and Stengers 1984), computer science (Holland 1995; Simon 1962), physics (Gell-Mann 1995), and economics (Arthur 1989). Developments across disciplines over time resulted in a meta-theoretical framework within which several theoretically consistent approaches and methods can be integrated.

Complexity science theories and methods combine different epistemologies (i.e., positivism, interpretivism, and realism) to provide novel opportunities to question assumptions (e.g., equilibrium, stability, etc.), manage tensions and paradoxes, and rethink the way we view many sociotechnical phenomena at the center of our field. Their value is particularly prominent when the research community faces new phenomena and questions that do not lend themselves well to the traditional, reductionist approaches.

Complexity Drivers and States

Complexity is an attribute of systems made up of large numbers of diverse and interdependent agents[3] that influence each

[3]These could range from molecules to individual human beings to organized collectives.

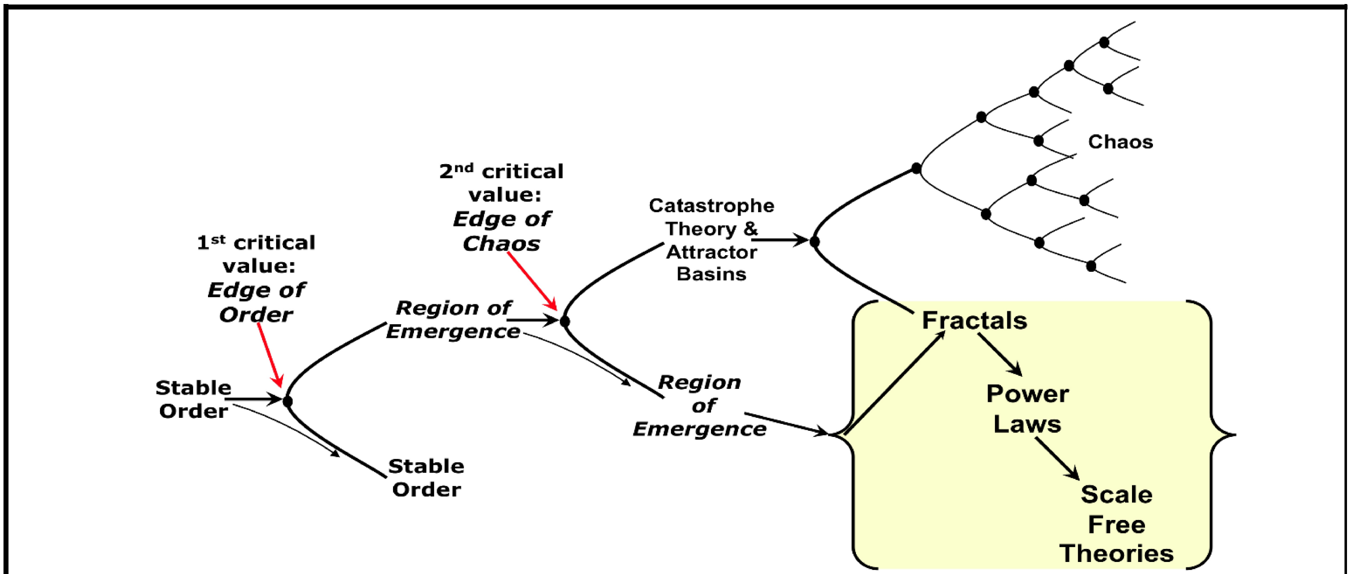

Figure 1. States of Complex Systems (Benbya and McKelvey 2011)

other in a nonlinear way and are constantly adapting to internal or external tensions (Holland 1995). Because such systems are constantly evolving, they have a large degree of unpredictability. They cannot, therefore, be understood by simply examining the properties of a system's components.

Four key characteristics influence the level of complexity in a system: (1) diversity, (2) adaptiveness, (3) connectedness, and (4) mutual dependency among agents in the system (e.g., Cilliers 1998; Holland 1995). The nonlinear interplay of the above four characteristics coupled with increased tension in the form of external or internal challenges and/or opportunities drive the system from one state to another.

A system can exist or fluctuate between three states or regions: stable at one extreme, chaos at the other, with an in-between state called the edge of chaos (Kauffman 1995; Lewin 1992). Figure 1 provides an illustration of the three states.

Specifically, in the stable state, the diversity, adaptiveness, connectedness,and mutual dependency of agents in the system are all at low levels. Consequently, adaptive tensions are low (Page 2010) and complexity is benign (Tanriverdi and Lim 2017). The system rapidly settles into a predictable and repetitive cycle of behavior. In such stable systems, novelty is rare. There is a tendency for stable systems to ossify.

As the diversity, adaptiveness, connectedness, and mutual dependency levels of systems reach moderate levels, the complexity level increases (Page 2010). Systems with increased levels of complexity enter the so-called "edge of chaos" state or a region of emergent complexity (Boisot and McKelvey 2010). By staying in this intermediate state, these systems never quite settle into a stable equilibrium but never quite fall apart. They exhibit continuous change, adaptation, coevolution and emergence (Kauffman 1993; Lewin 1992).

Increasing levels of tensions, beyond a certain threshold, might result in chaos or extreme outcomes (e.g., catastrophes, crises, etc.) which exhibit fractals, power laws, and scalable dynamics. Chaotic systems never really settle down into any observable patterns. Since they are sensitive to initial conditions, they can amplify exponentially and have monumental consequences (Gleick 1987).

Complexity Theories

As outlined above, many living systems (e.g., organisms, neural networks, ecosystems) on the edge of chaos appear to constantly adapt and self-organize to create configurations that ensure compatibility with an ever-changing environment. This perpetual fluidity is regarded as the norm in systems on the edge of chaos; it can lead to processes and outcomes as diverse as phase transitions, catastrophic failures, and unpredictable outcomes (see Table 1). Complexity theories such as emergence, coevolution, chaos, and extremes, as well as scalable dynamics, offer an explanation of such processes and outcomes.

Table 1. Processes and Outcomes of Complex Systems

Complexity Theories	*Processes*	*Outcomes*
Emergence	• Disequilibrium situations: tensions, triggers and small events outside the norm • Positive feedback and bursts of amplification • Phase-transitions • Self-organization	• Unpredictable outcomes: new structures, patterns, and properties within a system (e.g., distributed leadership emergence), a new level of analysis (e.g., a network), or a collective phenomenon (e.g., collective action) • Emergence can take two forms: composition or compilation
Coevolution	• Interdependency and boundary-crossing interrelationships • Multilevel dynamics • Bidirectional or two-way causality	• Mutual influences • Reciprocal adaptations and changes over time
Chaos	• Sensitivity to initial conditions • Constrained trajectory (e.g., strange attractor) • Time-dependency and irreversible dynamics	• Catastrophic failures (e.g., systemic risk, cyber-security breaches) • Escalation of causes leading to disastrous societal consequences (e.g., disrupting lives on a large scale)
Scalable Dynamics	• Instability and large variations • Single cause leading to a cascade of interconnected events	• Self-similarity across scales • Positive or negative extreme outcomes • Fractal dynamics • Power laws

Emergence

Emergence is a dynamic process of interactions among heterogeneous agents that unfolds and evolves over time, resulting in various kinds of unexpected novel individual- and group-level configurations and/or broader social structures (Benbya and McKelvey 2016). Complexity and organization scholars have theorized such a dynamic process for some time (Kozlowski et al. 2013; Plowman et al. 2007).

Systems-wide changes in natural open systems revealed how unorganized entities in a given system, subjected to an externally imposed tension, can engage in far-from-equilibrium dynamics. The entities can therefore self-organize into distinct phase transitions leading to a new higher-level order (Prigogine and Stengers 1984).

Social systems put under tension, through recession, crisis, organizational change, and so forth, can exhibit similar phase transitions and emergent outcomes. As such, many social scientists have made a direct mathematical parallel between physical and social systems to deduce the process mechanisms inherent in micro interaction dynamics that yield the higher-level order and its emergent novel outcomes. They have identified two forms of emergence: composition or compilation (Kozlowski and Klein 2000). In *composition* models, emergent processes allow individuals' perceptions, feelings, and behaviors to become similar to one another. *Compilation* models, on the other hand, capture divergence. They characterize processes in which lower-level phenomena are combined in complex and nonlinear ways to reflect unit-level phenomena that are not reducible to their constituent parts. The discovery of emergence involves either a *post hoc* analysis of time series data (e.g., system behavior) and conceptual tools that allow scholars to verify the existence of emergence dynamics in systems, or an analytical mapping of the sequential phases of emergence dynamics (e.g., Plowman et al. 2007).

Interactions among sociotechnical entities yield many emergent outcomes in information systems. Examples include the collaborative creation of online order and technology affordances (e.g., Nan and Lu 2014), IS alignment (Benbya et al. 2019), and new configurations among organization, platform, and participant dimensions (Benbya and Leidner 2018). An emergence perspective offers a lens to understand many unpredictable sociotechnical phenomena that span individual, group, organizational, and societal levels in the context of widening digitalization.

Coevolution

Coevolution refers to the simultaneous evolution of entities and their environments, whether these entities being organisms or organizations (McKelvey 2004). Ehrlich and

Raven (1964) introduced the term *coevolution* to characterize the mutual genetic evolution of butterflies, and associated plant species. Such a process encompasses the twin notions of interdependency and mutual adaptation, with the idea that species or organizations evolve in relation to their environments, while at the same time these environments evolve in relation to them.

In addition, to the above characteristics, coevolutionary processes have three main properties. First, coevolutionary phenomena are multilevel. They encompass at least two different levels of analysis. Second, coevolutionary phenomena take time to manifest. This implies that longitudinal designs are necessary to understand coevolutionary processes. Third, bidirectional causality or two-way relationships (e.g., Yan et al. 2019) are central to coevolutionary processes.

In IS research, coevolution theory has been used to theorize the codesign of organizations and information systems (Nissen and Jin 2007; Vidgen and Wang 2009), the alignment of business and IT (Benbya et al. 2019; Benbya and McKelvey 2006b; Tanriverdi, Rai, and Venkatraman 2010; Vessey and Ward 2013), coevolution of business strategy with the competitive landscape (Lee et al. 2010); and coevolution of platform architecture, governance, and environmental dynamics (Tiwana et al. 2010).

Chaos

Chaos theory was initially developed with Lorenz's (1963) work in response to an anomaly in atmospheric science. Chaotic systems are sensitive to initial conditions. This sensitivity to initial conditions, called the "butterfly effect," implies that even a slight change, analogous to a butterfly's wing-beat, can lead to radical consequences on a much larger scale.

In addition to being unstable and sensitive to initial conditions, chaotic systems are deterministic because the system's trajectory is constrained. Such chaotic systems possess a strange attractor, a value or a set of values that system variables tend toward over time but never quite reach (Lorenz 1963). Sudden discontinuous shifts in chaotic systems drive them from one attractor to another, leading thereby to catastrophes and disastrous societal consequences.

Chaos theory has been used to theorize social and organizational dynamics as nonlinear chaotic systems by virtue of their sensitivity to initial conditions. For example, McBride (2005) used concepts of chaos theory to study the dynamic interactions between information systems and their host organizations. Guo et al. (2009) use chaos theory to develop a framework to illustrate blog system dynamics arising from micro (individual blog traffic dynamics) and macro (blogosphere structure) levels. Hung and Tu (2014) provide an empirical analysis of the applicability of chaos theory to explain technological change processes. Tanriverdi and Lim (2017) theorize about IS-enabled complexity vigilance capabilities for detecting whether a complex ecosystem approaches the edge of chaos/discontinuity.

Scalable Dynamics, Fractals, and Power Laws

Scalable dynamics refer to self-similarity of underlying patterns across different levels of analysis (Manderbrot et al. 1983). This notion of self-similarity across scales has become a core tenet of complexity science and has led to various theories to characterize how a single cause can scale up into positive or negative extreme events and drive similar outcomes at multiple levels (for reviews, Adriani and McKelvey 2006; Benbya and McKelvey 2011).

The dimensionality of such self-similarity across scales can be measured using a mathematical mapping technique referred to as *fractals*. In other terms, fractals measure the "density" of a nonlinear data set, such as stock market behaviors or the shape of a coastline (Casti, 1994). When such measures are taken at increasing orders of magnitude, each fractal dimension is "self-similar" to the ones before and after it, meaning that the underlying patterns are the same across levels of analysis. These relationships are always governed by a power law (Cramer 1993).

Fractal analysis has helped describe and explain different changes that occur within similar patterns at multiple scales across organizations, markets, and industries. For example, Farjoun and Levin (2001) use a fractal analysis to characterize industry dynamism over time and capture the rate, amplitude, and unpredictability of change.

Methods

Research on complex sociotechnical systems has used a variety of methods, some are well established while others are just emerging. IS scholars have studied dynamics of complex systems by using established research methods such as longitudinal qualitative case studies (e.g., Benbya and Leidner 2018; Paul and McDaniel 2016), morphogenetic approaches (e.g., Njihia and Merali, 2013), statistical methods for longitudinal data analyses (e.g., Nan and Lu, 2014; Tanriverdi and Du 2020; Tanriverdi, Roumani, and Nwankpa 2019). However, complex sociotechnical systems that operate far from equilibrium conditions also present challenges for some established research methods such as closed-form analytical modeling methods. As such, newer methods have emerged to study under nonequilibrium conditions, complex interactions among multiple variables, and multilevel causality. Those new methods include agent-based simulation, the qualitative comparative analysis (QCA) method, and dynamic network modeling based on graph theories.

Agent-based simulation utilizes symbol-based computation to precisely express a theory about a complexity concept such as agents, interactions, and the environment involved in an emergent process. The computational expression can then be used to simulate and test the theory in controlled and replicable ways. This methodological approach was advanced by the Santa Fe Institute (SFI), a multidisciplinary research center created in the mid-1980s (Waldrop 1992). Applications of simulation methods include genetic algorithms (Holland 1995), cellular automata (Krugman 1996), NK landscape models (Kauffman 1993), and a combination of several approaches found in agent-based models (Carley and Svoboda 1996).

The QCA method allows researchers to identify how multiple causal attributes combine into distinct configurations to produce an outcome of interest, and to assess the relative importance of each configuration to the same outcome (Ragin and Rubinson 2009). It relies on the set-theoretic approach and Boolean algebra to conceptualize and analyze causal complexity described as "equifinality, conjunctural causation, and causal asymmetry" (Ragin 2000, p. 103). Scholars from different social science disciplines including the IS field have advocated the use of QCA to embrace causal complexity that is typical of social or sociotechnical systems (see El Sawy et al. 2010; Fichman 2004; Misangyi et al. 2017; Park et al. 2020).

Dynamic network modeling focuses on interactions that are the root cause of complexity in a phenomenon. Agents and their interactions are modeled as nodes and edges in a network. Dynamic network modeling enables researchers to identify patterns of interactions among a population of agents in a system. Scholars have been using tools like spatio-temporal network modeling to understand how new edges are formed (George et al. 2007; Taylor et al. 2010). For example, complex patterns of evolution in a digital platform ecosystem can be modeled as a network of third-party complements and boundary resources (Um et al. 2015). Here, third-party complementary products are modeled as agents interacting with one another through shared boundary resources. Scholars have used a similar approach to explore the relationship between consumers and brands (Zhang et al. 2016) and to understand the emergent nature of social relationships using relational event network (Schecter et al. 2017). Another important tool based on dynamic network modeling is network community (Sekara et al. 2016). A network community is set of densely connected nodes (Newman and Girvan 2004). For example, scholars have used network community to discover dynamic emerging patterns of routines (Pentland et al. 2020).

Implications of Complexity for IS Research

The increased levels of complexity in sociotechnical systems in the context of widening digitalization creates numerous opportunities and challenges for IS research. Due to the distinct effects of digital technologies on complex socio-technical systems, simply replicating middle-level theories and models for complex physical, biological, or social systems would not fully capture IS-specific complexity issues. A fruitful approach for IS researchers is to use complexity science as a meta-theoretical lens to rethink a few fundamental research challenges (see Table 2). In this section, we discuss a few of the challenges as exemplified by the following questions:

- Under what conditions is prediction feasible in complex, sociotechnical systems?
- What is the nature of causality in complex, socio-technical systems?
- How can researchers circumscribe the boundaries of a complex, sociotechnical system to study?
- How durable is newly discovered knowledge in complex, sociotechnical systems?

Limits to Prediction in Complex Sociotechnical Systems

Prediction of potential outcomes in a given sociotechnical system is one of the perennial questions in IS literature. It has become even more important with recent developments in big data and artificial intelligence (AI) technologies. However, complexity of sociotechnical systems present major challenges for prediction. Interactions among a diverse set of connected, mutually dependent, and adaptive agents in a sociotechnical system lead to the emergence of unexpected outcomes that defy the extrapolation techniques at the heart of prediction models. Properties of complex sociotechnical systems, such as nonlinearity, self-organization, coevolution,

Table 2. Implications of Complexity for IS Research

Issue	*Implication for IS Research*
Prediction of behaviors of complex systems	There are limits to the prediction of behaviors of complex sociotechnical systems. System-level properties such as non-decomposability, nonlinearity, self-organization, and coevolution inevitably lead to emergent, unpredictable system behaviors. Prediction efforts of IS research should focus not on the ability to foresee specific, well-defined system events in space and time (i.e., paths), but on the ability to anticipate the range of possible behaviors the system might adopt (i.e., patterns).
Nature of causality in complex systems	A linear view of causality between inputs and outputs of the complex sociotechnical system is inadequate. There are multiple causal mechanisms and different forms of causality in complex sociotechnical systems. Three distinguishing features of causality in complex sociotechnical systems are: (1) conjunction, which means that outcomes rarely have a single cause but rather result from the interdependence of multiple conditions; (2) equifinality, which entails more than one pathway from an input to an outcome; and (3) asymmetry, which implies that attributes found to be causally related in one context may be unrelated or even inversely related in another context.
Boundaries of complex systems	It is challenging to accurately circumscribe the boundaries of a complex sociotechnical system because complex systems are open systems. IS researchers can potentially address this challenge by building on Salthe's (1985) three-level specification in which agents of a complex sociotechnical system are defined by their components, a focal level of action, and by their contexts (Koestler 1978; Salthe 1989, 1985).
Durability of new knowledge claims in complex systems	Patterns of causal relationships in complex sociotechnical systems evolve over time. Thus, new knowledge discovered in one state of the system could be transient and inapplicable in another state of the system. In making claims to new knowledge in studies of complex sociotechnical system, IS researchers should report how frequently the system might be going through state changes and how durable the newly discovered knowledge might be. In addition, if the study time frame involves any phase transition of the complex system, researchers should report how the causal relationships might differ qualitatively before, during, and after the phase transition.

bifurcations, etc., lead inevitably to unpredictable states. Reductionist approaches that assume away some elements and interactions in the complex system could make formal prediction models feasible to implement. Although some behaviors of complex systems can be understood through formal models, those models cannot necessarily predict how a given system will evolve. Reductionist formal models also run the risk of generating biased, inaccurate predictions. This leads to an important question: Under what conditions is it feasible to make predictions in complex sociotechnical systems? Two observations can be made on this.

First, predictions in complex sociotechnical systems requires us to distinguish between patterns and path (Dooley and Van de Ven 2000). Path is the specific temporal trajectory, or set of points, that a system follows moment-by-moment; pattern is the distinctive (often visual) temporal shape that emerges when one views the path over a long period of time, plotted in a particular manner. Linear systems are predictable in both path and patterns. Chaotic systems are predictable in patterns, but not path (Bohm 1957). Although accurate prediction of a chaotic system's path through a space of possible states is very difficult because of sensitivity to initial conditions, clear overall patterns are nevertheless observable because the system's trajectory is constrained.

Second, apart from deterministic chaotic systems that remain predictable, what complexity science suggests is the inevitability of surprise (McDaniel 2004). Prediction becomes not the ability to foresee specific, well-defined events in space and time (i.e., path) but, at best, the ability to anticipate the range of possible behaviors the system might adopt (i.e., patterns). This then leads to the development of diverse configurations and states, or a portfolio of inter-related decision strategies that can be employed, as future possibilities unfold to become current realities. While predictability remains limited given complexity, anticipation remains fluid with respect to changing conditions and tensions, thereby facilitating adaptive action and survival (Boisot and McKelvey 2007).

Nature of Causality in Complex Sociotechnical Systems

The notion of causality is central to understanding the nature of interactions among heterogeneous elements in complex sociotechnical systems as the outcomes produced by such interactions (Sarker et al. 2019). Subsequently, the notion of causality is central to building theories for the IS discipline (Gregor and Hokorva 2011; Rivard 2014). Complexity science offers significant ways to extend prior thinking on the nature of causality in complex sociotechnical systems.

Conventional approaches dominant (explicitly or implicitly) in current models of thinking and analytical techniques, such as generalized linear models, often treat causality as an unobservable "black box," and focus on discovering whether there is a systematic relationship between inputs and outputs by relying on additive, unifinal, and symmetric notions of causality (Fiss 2007; Meyer et al. 2005; Mohr 1996). Such a linear view of causation remains limited and inadequate for explaining increased nonlinear interactions in digitized environments with processes such as coevolution, emergence, and self-organization as they involve multiple causal mechanisms and different forms of causality.

For instance, coevolutionary dynamics involve interactions among the components of a social system (such as a group, a community, or an organization), which in turn interacts with its environment. These multilevel interactions create or generate circular changes over time in one or several components of the system (Morgan 1923). In such contexts, unidirectional causation is not a good fit; rather, bidirectional causation, where the focus is on feedback dynamics in order to promote the key links among the components, is necessary (e.g., Yan et al. 2019).

Similarly, emergence, which spans multiple levels and leads to novel emergents, can be also envisioned as a positive feedback process starting with (1) bottom-up dynamic interaction among lower level entities (i.e., individuals, teams, units) which—over time—yield phenomena that manifest at higher, collective levels, (upward causation) (Kozlowski et al. 2013), and (2) an emergent higher collective level that influences the components' behaviors on the lower level from which it simultaneously emerges (downward causation) (Campbell 1974; Kim 1992). Thus, complexity theory brings to light notions of multidirectional causality (e.g., upward, downward, and circular causality), uncertainty, and, hence, a sense of the multiplicity of possible outcomes.

Building on this insight, IS scholars need to account for complex causality with its three distinguishing features: (1) conjunction, which means that outcomes rarely have a single cause but rather result from the interdependence of multiple conditions; (2) equifinality, which entails more than one pathway to a given outcome; and (3) asymmetry, which implies that attributes found to be causally related in one context may be unrelated or even inversely related in another (Meyer et al. 1993).

Boundaries of a Complex System and Implications for Multilevel IS Research

Because complex sociotechnical systems are open systems, we cannot accurately determine the boundaries of the system. In order to model a system precisely, we, therefore, have to model each and every interaction in the system, each and every interaction with the environment—which is, of course, also complex—and each and every interaction in the history of the system (Cilliers 2001). Since there are also relationships with the environment specifying clearly where a boundary could be, this is not obvious. Salthe's (1985) three-level specification in which agents are defined by their components, a focal level of action, and their contexts (Koestler 1978; Salthe 1989, 1993) helps to address this endeavor.

According to this basic triadic specification, complex sociotechnical systems can be best described at three adjacent levels of interactions: (1) the level where we actually observe it, or where it can be meaningfully perceived (focal level); (2) its relations with the parts described at a lower level (usually, but not necessarily always, the next lower level); and (3) to take into account entities or processes at a higher level (also usually, but not always, the next higher level), in which the entities or processes observed at the focal level are embedded.

Such a perspective, therefore, suggests that in order to theorize complex sociotechnical outcomes across levels it is necessary to (1) articulate the emergent collective construct, a construct's lower-level entities, and the constraints at the higher level related to the role of a selective environment; (2) zoom in to consider both focal entities, interactions among lower-level entities their internal structures and functions and to zoom out to consider both the focal entities and their external contexts; and (3) specify what kinds of top-down influence or bottom-up process are potentially relevant and assess the likelihood of interaction among the different kinds.

Durability of New Knowledge Claims in Complex Sociotechnical Systems

As a complex sociotechnical system dynamically coevolves with changes in its environment and its constituent components, the pattern of causal relationships within the complex system can also evolve over time. This raises a question about the durability of new knowledge discovered about causal relationships in a complex sociotechnical system. Complexity science conceives the development of new knowledge on the causal relationships as an evolutionary process of proposing conjectures (blind variation) followed by the refutation (selective elimination) of those conjectures that are empirically falsified (Campbell 1974; Popper 1983). This implies that over time, based on the cumulative research on complex systems, the collective view of the phenomena reflects the improved validity of the findings until proven otherwise, while the more invalid ones are abandoned. If the states of a complex sociotechnical system change frequently, however, the newly discovered knowledge in one state of the system could be transient and not applicable to the next state of the system. Thus, in making claims to new knowledge in studies of a complex, dynamically evolving sociotechnical system, it is important for researchers to report how frequently the complex sociotechnical system might be going through state changes and how durable the newly discovered knowledge might be. If the findings about the complex sociotechnical system are consistent over time, the new knowledge could be valid and durable during that time period.

In addition, if a complex sociotechnical system goes through a phase transition, the existing roles, structures, and causal relationships in the system can dissipate and new ones can emerge, resulting in a qualitatively different set of causal relationships (Tanriverdi and Lim 2017). Thus, it is also important for researchers to assess if the study time frame involves any phase transition of the complex sociotechnical system, and how the causal relationships might differ qualitatively before, during, and after the phase transition. For example, Tanriverdi and Lim (2017) posit that qualitatively different types of IS capabilities are relevant to firm performance before, during, and after a phase transition of a complex sociotechnical system.

Background and the Contents of the Special Issue

This special issue is an outcome of on-going dialogues among IS scholars who have been interested in complexity. Initially, to bring together interested scholars and foster further interest, Tanriverdi, Nan, and Benbya organized research symposiums on managing in complex adaptive business systems. The inaugural symposium was held at the University of Texas at Austin (Austin, TX) in 2013. The second symposium was held at the University of British Columbia (Vancouver, Canada) in 2014. The third symposium was held at Montpellier Business School (Montpellier, France) in 2015. Then, Benbya, McKelvey, Nan, Tanriverdi, and Yoo organized a Professional Development Workshop entitled "Complexity in Information Systems and Digital Business" at the Academy of Management Meetings in Vancouver, Canada, in August 2015. On behalf of those who were involved in these symposia and workshops, McKelvey, Tanriverdi and Yoo proposed a special issue on complexity and subsequently agreed to serve as senior editors for the current special issue. In December 2015, Tanriverdi and Yoo organized a Pre-ICIS Paper Development Workshop for prospective authors who were interested in submitting their research to the special issue, where 26 extended abstracts were submitted and discussed with editorial board members.

The special issue received a total of 50 submissions. Forty submissions were sent out to review after the initial screening. In the next round, 22 submissions were invited for revision and resubmission. In the third round, 10 submission were invited for further revisions and resubmission. In the fourth round, seven submissions were invited for a final revision. In the final round, five articles were accepted for publication in the special issue. To recognize their involvement from the beginning of the entire process of the special issue development, Benbya and Nan joined Tanriverdi and Yoo in writing this introductory essay for the special issue.

The five articles in this special issue illustrate how IS scholars build on theoretical lenses and methodological tools of complexity science to study digitally induced complexity in sociotechnical systems. They demonstrate the promise for IS researchers to not only draw on but also extend complexity science in digital worlds. In discussing a special issue article, we first introduce the broad research theme motivated by a complex phenomenon and then discuss how the special issue article addressed some aspects of the phenomenon.

Research Theme 1: Designing IS to Unknown or Rapidly Changing Requirements

Although much IS research accounts for the degree of complexity inherent in IS development (ISD), it rests on the assumption that the ISD process can be rationally planned and controlled. Such an assumption, however, is not suitable for explaining rapid and unexpected changes characterizing the increasingly interconnected IS collectives found in contemporary organizations. Nor is it sufficient if we are to understand the generativity and emergent properties with which digital infrastructures and platforms are inextricably intertwined. This raises an important question for ISD in complex environments: *How do we design systems to be evolvable so as to match the transient pace of changing environments and organizational goals*? A number of IS scholars over the past few years have increasingly begun to consider the distinctive insights offered by complexity science to guide the development of evolvable and agile systems (e.g., Benbya and McKelvey 2006a, 2006b; Montealegre et al. 2014; Tiwana et al. 2010; Vidgen and Wang 2009).

In their article, "The Dynamics of Drift in Digitized Processes," Brian Pentland, Peng Liu, Waldemar Kremser, and Thorvald Hærem explore unexpectedly changing requirements in digitized business processes supported by digital technologies. They observe that incremental endogenous changes in a digitized business process can suddenly push the process to a state of self-organized criticality. Through a simulation, they show that endogenous changes in the process can lead to nonlinear bursts of complexity, causing a transformative phase change in the process. After the burst of complexity, they further find that the dominant pattern of digitized business processes looks much different from the initial condition. Their finding raises significant questions about the way we design digital technologies to support digitized business processes. Their simulation results show that systems with adaptive programming are prone to transformative phase changes while systems with deterministic programming are not. Although it is infeasible to predict emergent process requirements, authors argue that digital technology can be designed and used to influence the likelihood and severity of transformative phase changes caused by emerging requirements in digitized business processes.

Research Theme 2: Using Digital Technologies to Steer a Complex Sociotechnical System Through Phase Transitions

Digitally induced, evolutionary transformative phase transitions also take place in products, business models, and new organizational forms. Some firms embed digital technologies in physical products to transition from physical products to digitized products (Tarafdar and Tanriverdi, 2018; Yoo et al. 2010). Some firms transition from a portfolio of digitized products to a product platform over which they develop an offer of a family of derivative digital products (Gawer 2014). The pervasiveness of digital technologies in products also leads to the development of new business models around digital platforms and ecosystems (Yoo et al. 2012). Some firms want to transition from competing on products to competing on digital platform ecosystems (Parker et al. 2016). They seek to transition toward multi-sided digital platform ecosystems that can solve common problems of very large numbers of consumers and third-party content developers. Such transitions also emerge in IT-enabled organizational forms, such as communities and markets, which can dynamically transform over time. Benbya et al. (2015), for example, theorize about how a market can transition into a community, and vice versa. Rather than conceptualizing these forms as alternative, stable structures of knowledge sharing and innovation, they call for investigating movements and transitions between them. These transition endeavors raise an important question for IS research: *How can firms use digital technologies to deliberately steer a complex sociotechnical system from a given state through phase transitions toward a desired new state*?

In their article, "Digitization and Phase Transitions in Platform Organizing Logics: Evidence from the Process Automation Industry," Johan Sandberg, Jonny Holmström, and Kalle Lyytinen address this question by conducting a longitudinal case study of digitally induced transformative phase transitions in ASEA Brown Boweri (ABB). Specifically, they study how ABB started with an analog automation product platform, infused it with digital technologies deepening its digital capacities over a 40-year period, and tried to steer it toward an ecosystem-centered organizing logic. Sandberg and his colleagues use the constrained generating procedures (CGPs) notion of the complex adaptive systems theory to analyze three mechanisms of phase transitions: interaction rules, design control, and stimuli-response variety. The findings suggest that firms can leverage digital technologies in trying to deliberately steer complex sociotechnical systems through phase transitions toward desired new states. However, the outcomes of digitally induced phase transitions are not easily foreseen as they are often mediated by unintended, emergent changes in CGPs.

Research Theme 3: Understanding How Complex Institutional Structures Shape the Evolution of Enterprise Information Systems

A major desire of organizations is to foresee how their digital or nondigital interventions would affect the evolution of their enterprise information systems and performance outcomes. However, due to the complexity of their institutional environments, such outcomes are often emergent and infeasible to foresee. Nevertheless, complexity scholars and practitioners suggest modeling and simulating such complex environments to gain insights into possible evolution patterns of enterprise IS and performance outcomes.

In "The Evolution of Information Systems Architecture: An Agent-Based Simulation Model," Kazem Haki, Jannis Beese, Stephan Aier, and Robert Winter build a theory-informed agent-based simulation model to generate insights about the evolution of enterprise IS architecture and efficiency and flexibility outcomes in complex institutional contexts. Specifically, they model the complex institutional environments of organizations by modeling three institutional forces (i.e., normative, coercive, and mimetic forces), and creating different combinations of the institutional forces. They also model how a heterogeneous set of agents (e.g., individuals and organizational units) would interact with the institutional forces in trying to complete a dynamically changing set of tasks in the environment. The dynamic changes in the task environment influence how agents would interact with each other and with the institutional forces and whether they would adopt standardized IT solutions of the corporation or develop customized IT solutions locally to address the tasks. Haki and his colleagues conduct simulations to understand how the enterprise IS architecture of the organization would evolve under different levels and combinations of the institutional forces and what kinds of efficiency and flexibility outcomes could be expected. This study illustrates how IS researchers use the theoretical and methodological tools of complexity science to help managers anticipate how complex institutional environments of their organizations could shape the evolution of their enterprise IS architectures and organizations' performance outcomes.

Research Theme 4: Taming Complexity with Algorithms

Complexity science argues that problems emerging out of the complexity of sociotechnical systems are "wicked" problems that cannot be "solved" but that they could be "tamed" (Tanriverdi, Rai, and Venkatraman 2010). A wicked problem has a large number of diverse stakeholders who have different objectives, values, and priorities. Those stakeholders are connected and mutually dependent. A wicked problem emerging out of digitally induced complexity in digital platform ecosystems is a search problem. The search behavior of one stakeholder affects search outcomes of the other stakeholders. The roots of the wicked search problem are tangled. The wicked problem morphs into another form with every attempt to address it. The challenge has no precedent. There is nothing to indicate that there is a right answer to the wicked search problem. While it is infeasible to solve such wicked problems, IS researchers turn to big data, machine learning, and AI algorithms to "tame" them.

Onkar Malgonde, He Zhang, Balaji Padmanabhan, and Moez Limayem, in their article "Taming Complexity in Search Matching: Two-Sided Recommender Systems on Digital Platforms," develop a complexity theoretic recommender algorithm to address the wicked search matching problem arising out of digitally induced complexity in Internet-based educational platforms. They view an Internet-based educational platform as a complex adaptive business system (CABS) where multiple sides of the platform have different and evolving objectives, preferences, and constraints. They argue that search matching is a wicked problem in such CABS and that it cannot be tamed by traditional one-sided recommender algorithms. They build on complex adaptive systems theory to develop a two-sided recommender algorithm for taming the complexity of the search matching problem by allowing agents to co-evolve and learn in the system. Using an agent-based simulation model, they show that the proposed recommendation algorithms tame the wicked search matching problem although it cannot fully solve it.

Research Theme 5: IT-Enabled Competitive Advantage in Complex Competitive Environments

IT and competitive advantage remains a key topic of interest to the IS discipline. As the complexity of competitive environment increased, however, firms started to find it increasingly challenging to achieve their quest for competitive advantage. Rivals and new start-ups use digital technologies in innovative new ways to make frequent and bold competitive moves to erode the advantages of the incumbents. As incumbents attempt to renew their advantages, the performance rank orderings of firms in the industry keep fluctuating rapidly, a phenomenon known as hypercompetition (Nan and Tanriverdi 2017). As such, the traditional quest of sustained competitive advantage ought to shift to a quest to create and renew temporary competitive advantages in complex, hypercompetitive environments (Tanriverdi, Rai, and Venkatraman 2010). Some scholars argue that firms can cope with such environments by developing IT-enabled dynamic and improvisational capabilities and IT-enabled agility (El Sawy and Pavlou 2008; Pavlou and El Sawy 2010). Other scholars argue that adaptation to a rapidly changing environment may not be sufficient for firm survival and performance. Coevolutionary views of IS strategy have been proposed to better account for the mutual influences of a firm's IT-based strategic actions in complex, dynamically changing environments (Benbya and McKelvey 2006a, 2006b).

Concomittant with these trends, economists warn that some firms, especially the leaders of digital platform ecosystems, enjoy rising monopoly power and persistently high monopoly profits. There have also been reports of declining dynamism and competition in the U.S. economy (Shambaugh et al. 2018). Since the era of personal computers in the 1980s, there has been a marked increase in concentration rates and a decrease in competition in the United States (Eggertsson et al. 2018). After the take-off of the Internet in the mid-1990s, concentration rates have been rising faster in high IT-intensive industries than in low IT-intensive industries (McAfee and Brynjolfsson 2008). The highest concentration rates are seen in industries characterized by digital technologies that have large returns to scale and network effects (Shambaugh et al. 2018). The gap between winners and losers has also widened dramatically. These seemingly conflicting trends raise important questions for IS strategy research: Does digitalization amplify hypercompetition and erode the IT-enabled sources of sustained competitive advantages? Alternatively, does digitalization attenuate hyper-competition by concentrating the ownership and control of digitalized resources and market power in a few digital giants, thereby reducing rivalry? If both scenarios are feasible, how can firms strategize to create competitive advantages with IT?

YoungKi Park and Sunil Mithas, in their article "Organized Complexity of Digital Business Strategy: A Configurational Perspective," examine how firms configure their six key digital and nondigital capabilities to achieve high performance in complex digital environments. They use a configurational perspective and a fuzzy-set qualitative comparative analysis (fsQCA) method to study how different configurations of the complex, nonlinear relationships among the six digital and nondigital capabilities affect firm performance in different economic sectors with varying digitization and environmental turbulence levels. A key finding is that digital capability alone is neither necessary nor sufficient for high performance in any configuration. However, digital capability is an important element of the overall capability configuration. Depending on the economic sector, digital capability plays different roles in the overall capability configuration; for example, no role at all, a counterproductive role, or a high contributor to performance.

Conclusions

Digitally induced complexity is pervasive in sociotechnical systems. Complexity presents fundamental challenges to IS research such as the difficulty in circumscribing the boundaries of a complex system, the multilevel nature of the complex phenomena, the difficulty of causal inference, the limited durability of new knowledge claims, and the limits to predictability. Nevertheless, complexity science offers theoretical and methodological tools to address these challenges and turn them into opportunities. The five articles in this special issue illustrate how IS researchers use the theoretical and methodological tools of complexity science to study wicked problems arising out of digitally induced complexity in the digital world. Each of these special issue articles recognizes that the new complex phenomenon it focuses on would not have been feasible to study with conventional theories and methods. By building on theories and methods from complexity science, these studies were able to study the complex new phenomena and generate new insights and explanations. However, these articles are not mere applications of known complexity concepts in the IS context. They also leverage the uniqueness of the IS context to generate new insights to contribute back to complexity science. Specifically, these IS studies inform complexity science how the digitally enabled hyper-connections, hyper-speed, and hyper-turbulence in sociotechnical systems create previously unprecedented levels of complexity and dynamism and pose fundamental challenges to individuals, organizations, and society. In the natural and biological worlds studied by complexity science, major evolutionary and transformative changes take millions of years to unfold. In comparison, major evolutionary and transformative changes trigged by digitally induced complexity take place in a matter of years, if not months, days, and even hours in modern day sociotechnical systems. The articles in the special issue leveraged the unique properties of digital technologies, digitized processes, products, platforms, ecosystems, and business models to study how and why these transformations take place. They also combined their theories and methods with those of complexity science to generate new explanations as to how wicked problems created by digitally induced complexity could be tamed. The approaches developed by these IS studies could potentially inform complexity studies in other disciples.

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