

The future is now: calling for a focus on temporal issues in information system research

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Abstract

Purpose – As information systems (IS) phenomena continue to emerge and evolve in our ever-changing economic and social contexts, researchers need to increase their focus on time in order to enrich our theories. The purpose of this paper is to present broad suggestions for IS researchers about how they can direct some of their research efforts to consider, conceptualize and incorporate time into research endeavors and how they might be mindful about considering and specifying time-related scope conditions of their research efforts.

Design/methodology/approach – The authors synthesize empirical studies and discuss three distinct yet related frameworks of time and the benefits they can provide. The authors choose two research streams that reflect dynamic economic and social contexts – namely, enterprise systems and social networks – to illustrate how time and frameworks of time can be leveraged in our theory development and research design.

Findings – The authors demonstrate that limited research in IS has incorporated a rich conceptualization and/or discussion of time. The authors build on this gap to highlight guidelines that researchers can adopt to enrich their view of time.

Originality/value – Given the dynamic nature of IS phenomena and the increased availability of longitudinal data, the authors' suggestions aim to urge and guide IS researchers about ways in which they can incorporate time into their theory and study designs.

Keywords Time, Conceptualization of time, IS phenomena

Paper type Conceptual paper

Introduction

Information systems (IS) is a relatively young field that is coming into its own in terms of establishing a core body of knowledge around technology-related phenomena. Despite the growing body of knowledge, much of our work, especially early research in the field, particularly that involving primary data collection efforts, has been based on cross-sectional studies. This stands to reason given that the initial forays into the understanding of any phenomenon tends to be a series of snapshots toward increasing our understanding based on cross-sectional studies. Most IS theories and studies have black boxed time (i.e. do not specify when they are valid) or treat time in a coarse manner, relying almost exclusively on linear, rather than other richer, theoretical conceptualizations of time or the occurrences of an event. For instance, Khan and Jarvenpaa (2010) conceptualized time by treating it as before vs after an event is



scheduled online to study the behavior of online groups. Venkatesh and his colleagues used the passage of chronological time from the initial use of target technology to represent experience (Venkatesh *et al.*, 2003, 2012). Bhattacharjee and Premkumar (2004) conceptualized time by treating it as pre- vs post-adoption. Likewise, other works use the theoretical ideas related to time as framed by dynamic IS phenomena, such as IS implementation stages, but their contextual description of studies does not capture an assessment of the start and end of stages (e.g. Sykes and Venkatesh, 2017), and especially not related to rich conceptualizations of time that we will discuss later.

Except for few recent studies (e.g. Ghose and Todri-Adamopoulos, 2016; Thompson *et al.*, 2020; Venkatesh *et al.*, 2020), the majority of empirical IS studies use time from a methodological perspective to *merely* strengthen causal claims (e.g. use of longitudinal datasets). This dominant use of time captures longitudinal data for method/rigor purposes. For instance, Bao *et al.* (2020) use a 12-year dataset to examine the relationship between patient portal use and health outcomes. An emphasis on establishing causality over time, with time as a central *concept*, can build a solid foundation to inform our understanding of antecedents and consequences of IS-related phenomena, rather than simply being used as a methodological strength or weakness.

Several scholars in management provide rich conceptualizations of what the concept of time means and demonstrate that time itself is a rich construct whose definition and relationship to events can vary a great deal depending on the context of study (see also Johns, 2006, 2018). Some rich conceptualizations of time do exist in IS research (Cooper and Zmud, 1990; Markus and Tanis, 2000; see also Zhu *et al.*, 2006b) but, for the most part, they have not been leveraged in theory development and study design. As a field matures, treating *time* as a central concept and construct is essential to our theory development and progress (see Ancona *et al.*, 2001; Poole, 2004; Poole and Van de Ven, 2004; Zaheer *et al.*, 1999). Considering the role of time in theory and research also directs our attention to process and underlying sequences (e.g. Havakor and Sabherwal, 2018; Jeyaraj and Sabherwal, 2008) to understand change. The IS field has long focused on process theories and has developed some compelling process frameworks (e.g. Sabherwal and Robey, 1995). More explicit attention to time can enhance process theories of IS as well (see Johns, 2018; Poole, 2004).

This paper presents a broad overview of the concept of *time* and how it can and should be leveraged in theory development and empirical research. First, we will discuss three potential gains that stem from incorporating time more systematically into IS research. Each gain is based on additional conceptual structures that must be introduced to incorporate time. We then illustrate these gains in two research streams that reflect dynamic IS phenomena, namely, enterprise system (ES) implementations and social networks [1], to suggest how each of the three benefits might advance theory and research. Given that technology and interactions involving social actors through/with technology are central to organizations in any field, we chose these two illustrative research streams. Finally, we end with some general recommendations on future steps to be taken to integrate temporal issues into IS research.

Benefits of considering time in is research

There are at least three benefits from explicitly considering time in IS research. First, an awareness of the perspective on time that they take can sensitize IS scholars to assumptions they are making about the nature of the processes they are investigating. McGrath and Kelly (1986) discuss four different perspectives on time. The first is *Newtonian time*, the reversible time of classical physics. This is often taken to be the default time in social science research generally, but, in fact, this perspective on time is

seldom used because in principle time can run backward as well as forward. Instead, McGrath and Kelly (1986) argue, a more common linear view of time in social science research is a second perspective on time that they call *dominant cultural time*, which takes the Newtonian view, but regards the flow of time as unidirectional and irreversible. This view assumes that time is continuous and can be measured, but corresponds to human experience of forward moving time.

A third perspective on time is *transaction time* in which time is demarcated into significant events, such as the cycle of Church holidays in medieval Europe. This view stresses the psychological perspective on time in which time is divided into units based on significant events. Rather than an objective uniform external measure of time, transaction time is demarcated either “from the inside” by what the participants indicate are significant events or “from the outside” by an observer who identifies significant events. The events themselves, rather than the “ruler of time,” provide the measure of time. Phases of an IS implementation and uses of IT across stages of the chronic care lifecycle (Thompson *et al.*, 2020) are examples of event time. Some transactional models of time, such as the calendar of Church holidays, incorporate cyclical models of time where events are recurrent.

Finally, there is *organizational time*, which combines the dominant cultural and transactional views. Organizational time is of particular interest for IS research because it incorporates a precise metric that enables the measurement of time elapsed with significant events that give time meaning. For example, an IS department’s year is “marked” by regular significant events, such as a budget deadline, monthly updates, daily backups and yearly reports, as well as by “one-off” events, such as the milestones set up for an enterprise resource planning (ERP) system implementation. The regular events provide rhythms for the department that have to be coordinated with the one-off events. Regular events also often comprise a cyclical time, rather than linear time moving incessantly into the future. Cycles often have a symbolic import that goes well beyond the functions of the steps that comprise them. So, for instance, a year-end report of an IS department’s activities during a difficult ERP system implementation might bring closure for the year and open up a “fresh” slate. Considering organizational time, then, brings into focus not only the importance of temporality in processes, but also the importance of meaning in demarcating time.

Adopting a particular perspective on time, thus, involves importing certain assumptions about the process that time scaffolds, such as whether it is linear or cyclic, and whether it is driven by objective, external forces or by perceptions and meanings or by both. Consciously thinking through our assumptions about time has the potential to yield theories that are better specified and more explicit. For instance, if we adopt the dominant cultural view of time, we are implicitly importing the assumption that time can be measured with equal intervals and that the length of the intervals matter. In contrast, the transaction time perspective assumes that events are the important demarcations of time, implicitly assuming that length of time between events does not matter. As our examples below illustrate, such differences in assumptions may have substantial impacts on theorizing, research design and methodology.

A second benefit is that time can be deployed as a construct in IS theories. There are at least three ways in which time can function as an IS construct (Poole, 2004 and Venkatesh *et al.* 2006). Time can serve as *variable* in an IS theory (e.g. Ghose and Todri-Adamopoulos, 2016; Im and Rai, 2014; Venkatesh *et al.*, 2020). When time is an independent variable, duration, velocity of change and acceleration of change can all be incorporated into theory. For example, we might compare incremental (slow and gradual) with “big bang” (high velocity change with short duration) implementation of ERP systems. When time is a dependent variable, the duration or passage of time indicates events. The amount of time during which an IS is used can be employed as a measure of implementation (Real and Poole, 2005). When

time is a moderating variable, the impact of other independent variables is assumed to change as a function of time (e.g. Im and Rai, 2014; Venkatesh *et al.*, 2020). ITs are often assumed to be less useful and less easy to use right after their development than when they have matured.

Time can also be a variable in terms of *temporal predispositions* of people, organizations and cultures. Individual predispositions that might impact IS include time urgency and temporal orientation to past, present or future (Waller *et al.*, 2001). Organizational predispositions include temporal orientation (Lawrence and Lorsch, 1967) and pace (Perlow *et al.*, 2002). Cultural predispositions include monochronic vs polychronic sense of time (Hall, 1983), temporal orientation (Jones, 1988) and pace (Levine, 1988). Little IS research has incorporated time as a variable, particularly in terms of temporal predispositions or social construction of time. Yet, it is clear that during activities, such as system development, implementation and management, participants are conscious of time and that the way in which participants view or construct time should affect these activities.

Time can, finally, be considered as or actually be *socially constructed*. Orlikowski and Yates (2002) develop a useful perspective on how structuration processes in organization, construct “a variety of temporal structures which in turn shape the temporal rhythm and form of their ongoing practices” (p. 684). These include schedules, project plans and project management documents (e.g. Yakura, 2002). In such cases, time may be co-constructed with other phenomena, such as implementation of the IS (for instance, is it taking place “on schedule,” in which case, schedule is used to demarcate time and reconstruction of the schedule reconstructs time).

A third benefit is that paying closer attention to time can enhance our methods for studying processes in IS. Zaheer *et al.* (1999) develop an insightful analysis of how time scales figure in organizational theory and research. They distinguish five different types of time scales: existence interval, validity interval, observation interval, recording interval and aggregation interval. The *existence interval* refers to “the length of time needed for one instance of the process, pattern, phenomenon, or event to occur or unfold” (p. 730). This interval may be objectively set – as in the case of the 24-h period for circadian rhythms – or socially constructed – as in the case of the time a law firm sets for junior associates to make “partner.” The *validity interval* refers to the time scale over which a theory holds. For example, circadian rhythms are assumed to hold for all days of the year or life of the organism in question. The *observation interval* refers to the amount of time the researcher devotes to studying the process, pattern, phenomenon or event. The *recording interval* is the length of time each record of the process, pattern, phenomenon or event spans. The choice of the recording interval influences the conclusions researchers can draw about the object of study: a recording interval of 1 minute will produce a very different depiction of the phenomenon than will one of hours or months. The *aggregation interval* represents the choice regarding “over what time scale the recorded information is to be aggregated for theorizing or testing theory about” the process, pattern, phenomenon or event (p. 731). In many cases, aggregating and recording intervals are the same, but if records are combined, then they are different. As with the recording interval, the length of the aggregation interval affects the view of the phenomenon researchers derive.

The first two of Zaheer *et al.*’s time scales pertain to how a phenomenon or process itself is theorized conceptually, whereas the last three refer to the researcher’s frame of reference. Zaheer *et al.* argue that the existence interval constrains the other intervals, whereas the aggregation and recording intervals are typically also constrained by the observation interval. Zaheer *et al.*’s framework highlights the complex set of choices researchers make in developing theories and designing studies. For instance, a researcher who is interested in understanding how employees cope with large-scale organizational change (i.e. those involving massive revamp of business processes like ES implementations) through social networks and the dynamics of coping can apply these intervals, as shown in Table 1. It is

Table 1.
Overview of time
intervals

Scale	Key characteristics	Key questions	IS example
Existence interval	<div><div>(1) Represents the length of time needed for an instance of coping with change</div><div>(2) Constrains the requirements for the sizes of other intervals</div></div>	<div><div>(1) What is the life span of the phenomenon?</div><div>(2) Is there any <i>a priori</i> theoretical specification of the phenomenon?</div><div>(3) Is there any <i>a priori</i> empirical observation of the phenomenon?</div><div>(4) Are there any stakeholders in the study context who may influence the specification of an existence interval?</div><div>(5) Can the existence interval be socially constructed?</div></div>	Coping with large-scale organizational change exists over the entire phases of an ES implementation, as change continues to challenge employees. However, coping will be different across phases
Validity interval	<div><div>(1) Encompasses the existence interval completely</div></div>	<div><div>(1) Is the validity interval of the theory known or delineated?</div><div>(2) Is the entire existence interval covered by a theory?</div><div>(3) Are different theories applicable for different parts of the existence interval?</div><div>(4) If there are multiple applicable theories, do they offer competing or complementary explanations?</div><div>(5) Is the meaning of the phenomenon consistent across these multiple theories?</div></div>	Employees will engage in coping through social networks over the entire duration of an ES implementation

(continued)

Scale	Key characteristics	Key questions	IS example
Observation interval	(1) Spans at least a single length of the existence interval (2) Spans at least a single length of the existence interval (3) Spans at least a single length of the existence interval (4) Spans at least a single length of the existence interval (5) Spans at least a single length of the existence interval	(1) What observation intervals have been studied? (2) Are prior observation intervals, if any, consistent? (3) What was the rationale for specifying the observation interval (e.g. convenience or accessibility to organizations)? (4) How do observation intervals map to validity intervals? (5) Can the observation interval extend beyond the validity interval (i.e. before its start and after its end)?	A researcher may observe coping in each phase of an ES implementation and identify boundaries among phases based on key organizations events (e.g. 4 months pre-implementation or when the announcement of change occurred and 6–8 months post-implementation)
Recording interval	(1) Represents frequency at which data about coping is collected (2) Represents frequency at which data about coping is collected (3) Represents frequency at which data about coping is collected (4) Represents frequency at which data about coping is collected (5) Represents frequency at which data about coping is collected	(1) How frequent will the data be recorded in the observation period? (2) Will the chosen frequency offer a rich view of the examined patterns? (3) How does recording frequency shape interpretation of the phenomenon? (4) Are prior recording intervals, if any, consistent? (5) What was the rationale for any prior recording intervals?	A researcher may record social network ties, as a form of coping with change, at the end or the beginning of each phase of an ES implementation
Aggregation interval	(1) Corresponds to the recording interval (2) Its maximum size is identified by the size of the observation interval (3) May be the same size as the recording interval (4) May be the same size as the recording interval (5) May be the same size as the recording interval	(1) Will aggregation at different time scales lead to different interpretation of the phenomenon? (2) Does the level and unit of data analysis coincide? (3) Can we reveal additional nuances by aggregating at different scales? (4) How many instances of the phenomenon to aggregate? (5) Does aggregation level correspond to the research question (i.e. annual phenomenon or health condition like pregnancy)?	A researcher may aggregate social network ties at the beginning and end of each ES implementation phase

Table 1.

particularly important to maintain consistency across the five intervals. For example, if the observation interval is shorter than the existence interval, the study will not observe the entire process.

In sum, more explicit attention to time in IS research can make IS scholars aware of critical assumptions that frame and may constrain their research, can introduce useful new constructs into IS research, can improve the research design in the study of IS processes and help develop richer understanding of the phenomenon. In the following sections, we will discuss two topics to illustrate the potential of time in shaping/reshaping IS scholarship:

ES implementation illustration

ESs, such as ERP systems, end-to-end supply chain management systems and electronic medical record systems, are complex and implementations of the same can take months or even years to complete. Such implementations promise enormous benefit, yet they fail at an alarming rate. IS researchers have devoted a great deal of attention to this important topic in business (e.g. Sykes and Venkatesh, 2017) and healthcare (e.g. Venkatesh *et al.*, 2011; Greenwood *et al.*, 2019) contexts. To this point, there has been a limited rich *conceptual* treatment of time in this stream of research.

Although most work in management focuses on time, as it frames phenomena under study, IS and their implementation actually play a role in framing time. For instance, in their seminal article, Markus and Tanis (2000) define the temporal boundaries related to an ES implementation in terms of different phases, i.e. chartering, project, shakedown and onward and upward, that in turn are defined by the specific activities that take place during each phase. The detailed description of the activities in each phase in Markus *et al.* (2000) frames ES development in terms of organization time. They specify phases in terms of accomplishments and boundaries of phases are set by accomplishing the major activities in the phase, while, at the same time, gauging ES rollout against a linear temporal scale. Because of this approach to defining phases, their boundaries are necessarily fuzzy – it is not necessarily clear when activities are complete and certainly activities in earlier phases are often revisited and reworked in later phases. Without questioning the utility of Markus *et al.*'s results, there are two ways in which more detailed consideration of time could sharpen the model and study, both with different implications. On the one hand, acknowledging that phases are events, not just periods of time would require identification of events that signaled phase transitions to participants. Participants might have been asked how they knew that the ES implementation had moved to a different phase or how they would know when they were ready to move out of their current phase. Events, such as kickoffs, evaluations or termination of consultants' contracts, might indicate phase transitions. Moving in a different direction, Markus *et al.* might acknowledge the fuzziness of phase boundaries and that phases are in part social constructions. This would involve adopting a dualistic notion of time in which the implementation itself unfolds in dominant cultural time as its activities are executed, but in which sensemaking about the implementation relies on transactional time to define key transition points and events that *post hoc* delimit phases.

The accounts of various organizations suggest that they adopted different temporal orientations to ES implementation. Some organizations adopted a future-oriented view of ES, thinking of them as ways to fully reconfigure their organizations and develop them in new directions, whereas others adopted a past-oriented view, trying to utilize the ES as a way to integrate existing operations and overcome previous problems. If temporal orientation were factored more explicitly into the study of an ES implementation, a logical step would be to gauge the temporal orientations of the major stakeholders and implementers. Waller *et al.* (2001) showed that the composition of groups in terms of temporal orientations led to different group processes and outcomes and could be expected to influence implementation.

Markus *et al.* (2000) found that success metrics were redefined throughout the implementation effort and differed from phase-to-phase. In the same vein that success is constructed by organizations, we would expect that time would be socially constructed. One critical feature of implementations is whether they have taken “too long,” and should be sped up, scaled back or even terminated because they are going too slowly. This sense of the length of time an implementation has taken vs the amount of time it should take is socially constructed during sensemaking about the implementation. Length of time is often understood in terms of temporal boundary objects that implementers utilize to plan and to coordinate their activities, such as project management plans. These can be used to set expectations about what amount of time each step of the process should take and hence become standards for judging whether something is “on schedule,” “taking too long,” “getting out of control,” and other judgments that affect not only how an ES is implemented, but also evaluations of success and failure.

Closer concern to time can also help IS scholars improve the design of studies of ES implementation processes. Studies on ERP system implementation in the shakedown phase (e.g. Morris and Venkatesh, 2010; Sykes, 2015; Sykes and Venkatesh, 2017) chose an observation interval that was defined in terms of culturally dominant time: 4 months pre-implementation and 6–8 months post-implementation. However, the contextual description of these studies does not provide the necessary information (e.g. *a priori* work or information from influential stakeholders, as suggested in Table 1) to help us assess whether the organization was indeed in the shakedown phase, that is, the existence interval of the shakedown phase was not specified.

Overall, researchers seldom specify the validity interval of their theories although they do tend to acknowledge that their study was conducted at a particular point in time that may bias the results. However, the bigger concern centers around researchers’ efforts to develop generalizable theories and consequently making gross generalizations about an ES implementation when, in reality, there are many differences across phases and activities within phases. Asking questions similar to those highlighted in Table 1 may be a good starting point.

Given that many ES implementations fail in the early stages, it is important to study them, with various activities taking place, through the phases in order to better understand the organizational, manager and employee activities and actions that contribute to success and failure. Likewise, it is important to understand the transitions from one phase to the next and the factors and actions that carry implementations over the hump. Although Markus and Tanis (2000) have articulated some of the common activities and mistakes in each phase, much work is necessary to develop a richer understanding of an implementation. In terms of Zaheer *et al.*’s notion of an existence interval, unless we theorize about and conduct studies over the lifecycle of an entire implementation, we cannot develop a complete understanding of the phenomenon and instead, we will be left with the type of understanding akin to what is reflected in the old tale of five blind men feeling different parts of an elephant and providing a technically accurate but holistically incorrect description of the elephant because each can only report based on the part of the elephant (i.e. tail, trunk, ear, leg and side) that he is actually touching. Although a holistic approach is important, we caution early career faculty members and PhD students from delving into this. We call for mid-career and senior scholars to engage in this endeavor to help enrich our field’s body of knowledge.

The existence interval of each phase is significantly shorter in terms of linear time than the existence interval of an entire implementation, thus making a phase much more feasible to study in terms of observation and recording periods. Theories should be developed that specifically incorporate the mechanisms and justification of the various activities that take place during a particular phase, i.e. actions by organizations, employees and IT staff. We expect that this would dictate very different explanations for observed behaviors and outcomes in different phases. Likewise, studies should be conducted such that the data collection relates well to specific phases based on activities, rather than just linear time. Thus, we advocate designing observation and recording

intervals that are carefully tied to the validity interval of the theory and empirical study. By doing so, researchers will explicitly specify the validity interval of theories and the empirical studies that test the proposed theories. In addition to developing a more accurate understanding of the phenomenon, this will greatly enhance our ability to compare findings and patterns across studies – i.e. an apples-and-apples comparison. It is possible that what would in the current approach of not specifying the validity interval be considered contradictory findings will be readily explained by the different validity intervals of different studies. Unlike the efforts to gain a holistic understanding, such efforts that are focused on specific phases are appropriate for PhD students and IS scholars in the early stages of their academic career.

A more nuanced view of an ES implementation can be gained by developing theories and designing studies that focus on specific slices or activities within a phase. It is likely the case that much cross-sectional research on an ES implementation falls in this category. However, seldom do researchers take advantage of the context and the unique value it can bring to theory development and in understanding where broader theories breakdown (Alvesson and Kärreman, 2007; Johns, 2006). Researchers studying a particular sub-phase of an ES implementation should leverage the activities and actions taking place at that time (e.g. requirements gathering in the project phase) in developing theory. As it relates to time, knowing more about the specific context of the study or *a priori* empirical work, as suggested in Table 1, will help create a theory with a more focused validity interval. This validity interval of the theory can then be juxtaposed with the observation and recording intervals to ensure that the data collected during such a study will allow for an appropriate test of the proposed theory given its validity interval. Such endeavors are also suitable for IS scholars at all stages of their career.

Social networks illustration

A network is a collection of connections between two or more entities (e.g. individuals, organizations and business units). Social networks, whether online or offline, have been studied in many disciplines, and they represent a research area that continues to get the attention of IS researchers and practitioners (Kane *et al.*, 2014; Sykes, *forthcoming*). Social networks can be examined in organizational settings as well as the broader social context. Within organizations, social networks map social ties between individuals. These face-to-face and technology-mediated networks depict various types of relationships and interactions, such as friendship or advice, in the individual level or the linkages between other entities at other levels of aggregation, such as teams, business units and organizations. In the broader social context, networking is typically technology-mediated and include such things as networking services (e.g. LinkedIn and Facebook), online health-care communities (Yan and Tan, 2017) and organizational online communities, wherein individuals, through the process of sharing information and experiences with the group, learn from each other and have an opportunity to develop themselves personally and professionally (Kim *et al.*, 2018).

Both types of social networks research would benefit from a focus on time to develop rich theory to further our understanding of various aspects of the core underlying phenomena. Although commonly understood that social networks of individuals, like attitudes and behaviors, are not necessarily static, it has only been recently that attention has been focused on the dynamic nature of such networks. Except for few empirical studies (e.g. Kalish *et al.*, 2015), the vast majority of social networks research in various fields, such as sociology, management and communication, is based on deriving networks from data treated, as network was a static phenomenon. Such a treatment is understandable in the study of relatively stable social structures that change relatively slowly over years, such as those theorized by sociologists. However, in the constantly evolving realm of IS, where even physical networks are rewired constantly and mobile communication is enabling dynamic

networks of devices and people, the assumptions that networks are stable and stationary is much less tenable.

Bringing time into the study of IS-mediated networks will strengthen our understanding of IS enabled networks and other phenomena, such as the impact of social networks on system development. Just as is the case for IS implementation, considering a temporal perspective more consciously could result in more reflective research on networks and IS. For example, [Putzke *et al.* \(2010\)](#) adopt dominant cultural time in their study of the evolution of participation in a massive multiplayer online game. They divide six months of data into three equal segments of two months each and trace changes in the community. This is a reasonable approach, but it also makes the assumption that phases all have equal lengths that is embedded in dominant cultural time that views time as a continuum that can be segmented into equivalent units (seconds, months, etc.). In studying ES implementation success, [Sasidharan *et al.* \(2012\)](#) also made assumptions about the time period that an organization needs to realize value from the system and organized their data collection on that basis. [Ridings and Wasko \(2010\)](#), in contrast, take the perspective of organizational time in their study of an online community. They divide the development of the community into six organically distinct phases of different lengths, demarcated by key events that occurred during the phases, which form a temporal progression. Just as Putzke *et al.* may have made limiting assumptions about phases in their view of time, Ridings and Wasko's demarcation of phases may have resulted in overlooking network dynamics that operate in "clock," rather than "event" time.

Time can also serve as a construct in IS network research (e.g. [Venkatesh *et al.*, \(2020\)](#)). One interesting construct from organizational behavioral research is temporal embeddedness, which should shape the existence intervals of networks and the evolution and/or dynamics of the social networks. It has been shown that a good predictor of behavior is previous behavior. Similarly, temporal embeddedness is the sense of expected future exchange/contact between nodes that have had contact with one another in the past ([Buskens, 2002](#)), as [Hahn *et al.* \(2008\)](#) found among system developers in project teams. Thus, it is a temporal dimension that encompasses both the past and future. However, in what configuration? What factors increase the potency of temporal embeddedness or reduce its effects? What are the effects of temporal embeddedness on characteristics of the social network participants, such as trust ([Riegelsberger *et al.*, 2007](#)) and job performance ([van Emmerik and Sanders, 2004](#))? Future work should work to develop a better understanding of exactly how temporal embeddedness influences social network ties. By understanding this pattern, researchers would be better able to predict future behavior.

A related, yet distinct, concept is that of the co-evolution of social network ties and entity (here, individual) behavior. As the implementation of an IS is a dynamic process, so too are the social influences that surround us – i.e. social network ties are rarely stagnant. Individuals create, sustain and dissolve social contacts continuously as needs arise and conditions change. Social ties change over time and in response to factors, such as those found in the organizational environment, e.g. the implementation of new technologies within an organization. Both dynamic elements, the social ties and the behavior, change over time and cause further changes in the one another. Understanding these recursive relationships will allow us to expand our understanding of social influence on behaviors of interest, such as technology use/adoption and employee cyberloafing. Except for empirical studies in other disciplines (e.g. [Kalish *et al.*, 2015](#)), the techniques for examining social ties have been largely static ([Robert *et al.*, 2008](#)). One reason for this is the nature of how researchers design studies, namely cross-sectional primary data collection efforts and/or snapshot secondary data use. Another reason is that the techniques for dealing with network and behavioral co-evolution have been limited ([Snijders *et al.*, 2010](#)) and used relatively recent in empirical research (e.g. [Kalish *et al.*, 2015](#)).

In the case of technology adoption and use, IS researchers examined social influences in the form of employee social networks (e.g. [Sykes et al., 2009](#); [Sykes and Venkatesh, 2017](#)). Yet, little has been done to understand the evolution of social network ties throughout the technology implementation cycle (the existence interval monitoring sustained use of a new implementation). Relating the ideas here to the previous illustration on ES implementations, the element of time is important in this context, given our limited understanding of social structures when the adoption becomes acceptance, or when acceptance becomes sustained use or when implementation goes from project to chartering to shakedown to onward and upward phases. Examining factors that influence choices and behaviors over time is an important next step in the development of our understanding in these areas.

Current research horizons have touched on the importance of online communities, such as recommendation communities and online social networking sites that have changed the way in which people interact within organizations and society in general ([Kane et al., 2014](#); [Kim et al., 2018](#); [Ridings and Wasko, 2010](#); [Yan and Tan, 2017](#)). In technology-mediated social networks, trust, for instance, still exist, but the rules that apply are often different ([Kane et al., 2014](#)). For example, because of the different modalities of communication involved, actors must utilize different cues to make judgments in face-to-face interactions. For example, there are different bases of trusting others in real vs virtual environments. How do these decisions change over time? What are the factors influencing the decisions that are more or less salient over time? Further, what is the existence interval for online communities of practice and groups within social networking sites? Temporal components addressing such questions should be included in our theorizing in this area to give us a more holistic understanding of the phenomenon.

Several tools for analysis of longitudinal examination of social networks have emerged. SIENA ([Snijders et al., 2010](#)), i.e. Simulation Investigation for Empirical Network Analysis, is a software predominantly used for analyzing network data, specifically social networks. SIENA can be used to analyze multiple types of dependent variables: longitudinal network, longitudinal network and nodal characteristics (e.g. individual behaviors) and cross-sectional network data. SIENA takes an actor-oriented focus when analyzing network and network and behavior longitudinal data and uses Markov Chain Monte Carlo modeling techniques to evaluate networks at different points in time. SIENA, version 4 or RSIENA, version 1.2–25, is a component in the R statistical program. Using SIENA to analyze networks will help us to understand how nodal characteristics influence the structures of a social network and vice versa. For example, we can analyze a face-to-face advice network within an organization and gain understanding of how behaviors (e.g. technology use) influence advice tie creation. It will also allow us to study how the social structures in turn influence future technology use. We will be able to map such information to temporal frameworks, such as [Markus and Tanis' \(2000\)](#) phases of ES implementation and [Ridings and Wasko's \(2010\)](#) phases of community evolution that, in turn, will significantly increase our holistic understanding of the phenomenon.

SIENA makes the assumption that the process generating temporal change is stationary, that is, that the same generator holds for the entire temporal period. A different approach developed by [Mucha et al. \(2010\)](#), multislice community detection, enables researchers to detect groupings in a series of temporal snapshots of networks (say each week for a year). The algorithm derives a quality function for reproduction of empirical adjacency matrixes based on the coupling of matrixes to those immediately preceding and following it in time, and can show how groups combine and split over time. This approach can detect structure in networks, as it changes over time and enables us to find modular networks within a larger network data set.

There are also several packages for visualizing longitudinal network data. [Bender-deMoll et al. \(2008\)](#) have developed rSoNIA, a framework for expressing, storing and manipulating information about networks that change over time. It can be used to create animations of

network dynamics. [Trier's \(2008\)](#) Commetrix also creates animated graphs for exploratory analysis. These packages, in conjunction with packages like SIENA, will greatly help enhance our understanding of the evolution of social networks in different contexts.

Consideration of time scales in research design can also inform IS research on networks. In studying change in networks over time, it is important to theoretically specify or empirically determine the existence interval of a network phenomenon and ensure that the observation interval corresponds to it. In their study, [Putzke et al. \(2010\)](#), for example, assume a two-month timeframe is sufficient to stabilize interactions among game players. It is likely that interactions stabilize more quickly than this (some studies suggest norms for interaction establish themselves within a few minutes in small groups, cf. [Gersick, 1988](#)), so their observation interval is longer than the likely existence interval, which is desirable for longitudinal research designs. Their recording interval is quite short, consisting of one instance of game play together, but these are aggregated over the two-month period, yielding a rather long aggregation interval. It is likely that this aggregation approach may hide variations in networks that occur over the aggregation period, so a test of whether there is any hidden variation would be desirable. Such an evaluation might be conducted using either of the dynamic visualization applications discussed above. [Table 2](#) summarizes an application of time intervals to some of the discussed studies.

Example study	Existence interval	Validity interval	Observation interval	Recording interval	Aggregation interval
Ghose and Todri-Adamopoulos (2016)	Unknown	6 months	6 months	6 months (multiple advertisement exposures for up to 20 min per exposure)	Aggregation pre- and post-exposure to advertisements for each individual within 6 months
Im et al. (2013)	Unknown	4 years	9 years	9 years	Annual aggregation for a period of 9 years
Putzke et al. (2010)	Unknown	6 months	6 months	3 periods of 2 months	3 periods of 2 months
Sykes and Venkatesh (2017)	Unknown	Unknown	12 months	6 months pre-implementation and 6 months post-implementation	6 months pre-implementation and 6 months post-implementation
Venkatesh et al. (2003)	Unknown	Unknown	6 months	3 periods within 6 months	Partial aggregation of 3 periods within 6 months
Venkatesh et al. (2008)	Unknown	Unknown	1 year	Four recordings every three months	Aggregation within each three-month period
Venkatesh et al. (2011)	Unknown	Unknown	1 year	Three recordings within a year	Annual aggregation
Venkatesh et al. (2012)	Unknown	Unknown	4 months	Two recordings within a period of 4 months	One aggregation of two data recording points
Venkatesh et al. (2016)	1 year	1 year	7 years	Annual recording for a period of 7 years	Annual aggregation for a period of 7 years
Venkatesh et al. (2020)	7 years	7 years	7 years	Annual recording for a period of 7 years	Annual aggregation for a period of 7 years

Table 2.
Time intervals in a
sample of IS studies

Conclusion

We discussed the important role that time plays in shaping IS-related phenomena and how IS phenomena in turn shape time. We call for IS scholars to focus their attention on the important construct of *time* to advance our understanding of IS phenomena that continue to emerge and evolve in various social and economic contexts. To illustrate the potential insights and advances an increased focus on time could yield, we illustrated issues and questions in two IS topics: ES implementation and social networks. However, the role of time is relevant to many phenomena and is essential to further the richness of IS theories, much as was the case with calls for research issued to management scholars to focus on time in theorizing. Based on our discussion, we offer a few broad suggestions to IS scholars. [Table 3](#) provides an overview of these suggestions that we elaborate on below:

- (1) *Examine phenomena longitudinally*: Given that we have underscored the importance of time in IS research, we call for IS researchers, particularly senior scholars, to examine phenomena longitudinally. The various conceptual frames discussed in this commentary, particularly the perspectives on time defined by [McGrath and Kelly \(1986\)](#) and the various time intervals defined by [Zaheer et al. \(1999\)](#), can help to inform theory, research design and analysis of longitudinal data. The availability of databases that contain longitudinal datasets, such as the records of messaging activity in online communities ([Ridings and Wasko, 2010](#)), electronic health records ([Kohli and Tan, 2016](#)) and game play behavior ([Putzke et al., 2010](#)), makes rigorous longitudinal study much easier than in studies based on more traditional methods. However, scholars should not confine themselves only to “ready-made” datasets. It remains important to study processes as they unfold in real time or through historical reconstruction. For instance, [Zhu et al. \(2006a\)](#) used an interesting international data

Opportunity/recommendation	Relevant time views	Example
1. Examine phenomena longitudinally	(1) Time intervals (2) Newtonian time (3) Dominant cultural time (4) Transaction time (5) Organization time	Combine longitudinal medical records with technology use datasets to theorize about and examine patterns in technology use in relation to disease or pandemic stages
2. Articulate assumptions about time from a theoretical perspective	(1) Time interval	Explain the assumption underlying existence interval for online communities providing support throughout stages of a particular disease or pandemic
3. Articulate assumptions about time from a methodological perspective	(1) Dominant cultural time (2) Organization time (3) Transaction time	Explain the fit between transaction time and sequence analysis when examining progress in disease stages
4. Consider the role of time to resolve consistencies in an existing body of knowledge	(1) Validity interval	Examine the effects of technology interventions throughout all stages of diseases or pandemic stages
5. Develop IS-specific constructs related to time	(1) Time as experienced by human beings (2) Time associated with information processing systems (3) Time associated with information (data) networks	Theorize the relationship among information processing in humans, data systems, and communication systems

Table 3.
Suggestions for IS
scholars

- set to understand standards diffusion. Longitudinal healthcare datasets (e.g. electronic health records) can also be combined or integrated with other data sources that capture interactions with technologies (e.g. mobile devices) over time.
- (2) *Articulate assumptions about time from a theoretical perspective:* Junior scholars, particularly faculty members pursuing tenure, should not view this article as legislating the conduct of longitudinal studies. Although longitudinal studies indeed have value, junior scholars can continue business-as-usual with two important caveats. First, it is important to specify the various time intervals explicitly so as to help others clearly understand the scope of the work (e.g. validity interval). Second, theory development should be done with careful consideration given to these scope conditions (e.g. validity interval) so that IS models and theories are consistent with the assumptions being made.
 - (3) *Articulate assumptions about time from a methodological perspective:* It is also important to recognize that research methods also incorporate assumptions about time. Various methods, such as time series and event history analysis, assume dominant cultural time with an underlying temporal continuum of equal interval. Sequence analysis (Saberwhal and Robey, 1995), Markov analysis (Poole et al., 2000) and phasic analysis (Poole et al., 2000) assume transaction time, time based on meaningful events. Most qualitative approaches (Langley, 1999) seem to assume organization time. Because of this, it is important for IS scholars to cultivate a variety of analytical approaches and to match the method with an appropriate conception of time.
 - (4) *Consider the role of time to resolve inconsistencies in an existing body of knowledge:* As IS as a field has accumulated knowledge in a variety of streams, a natural by-product of the accumulation of knowledge are inconsistent findings across studies. One way to resolve inconsistencies is by leveraging time and a variety of validity intervals to resolve such inconsistencies, as discussed earlier. One illustration of such work is Zhu et al. (2006b), who demonstrated that certain factors have a positive impact in the initiation stage, but can have a negative effect on assimilation of technologies in later stages. Further, researchers have used time to reveal dual causality in relationships that have been extensively studied in IS, such as IT use and firm size (Im et al., 2013). The interested reader is referred to Poole and Van de Ven (1989) for an extensive discourse on how time can be used in resolving paradoxes.
 - (5) *Develop IS-specific constructs related to time:* We would also recommend that IS scholars work to develop IS-specific constructs related to time. Because of its subject matter, IS research is mainly concerned with three kinds of time. In addition to time as experienced by human beings, there is time associated with information processing systems and time associated with information (data) networks. Time runs at different rates in these three realms. For information processing and communications systems, processes run in the millionths of seconds or even less. For data networks, processes run in hundredths of seconds or less. Human information processing runs in tenths of seconds or seconds. One important part of theorizing the IT artifact would involve theorizing the relationship among these three realms and its implications for IS design and effects. We expect such work to yield interesting insights and new avenues for scholarship.

Although our attention has focused primarily on clarifying assumptions about time and deploying them in theorizing (e.g. dominant cultural time, transaction time and organization time), using time as a construct (e.g. variable reflecting duration and velocity of change) and enhancing methods studying processes (e.g. existence interval and

validity intervals), the subject of time is much broader and can lead down still more paths. Some of the other aspects of time we might have considered include path-dependence and technological trajectories; the concept of *kairos* or appropriate timing, which the ancient Greeks believed was central to effective action; the phenomenology of time and multitasking, increasingly common due to IS. There simply wasn't time to get to all of them!

Note

1. We note that these streams are ones in which a subset of the authors of this paper have been closely involved and some of the works cited here refer to those papers. We were particularly well positioned to reflect not only on the description of the role of time, but also on our thought process underlying the conceptualization and operationalization of time.

References

- Alvesson, M. and Kärreman, D. (2007), "Constructing mystery: empirical matters in theory development", *Academy of Management Review*, Vol. 32 No. 4, pp. 1265-1281.
- Ancona, D.G., Goodman, P.S., Lawrence, B.S. and Tushman, M.L. (2001), "Time: a new research lens", *Academy of Management Review*, Vol. 26 No. 4, pp. 645-663.
- Bao, C., Bardhan, I., Singh, H., Meyer, B. and Kirksey, K. (2020), "Patient-provider engagement and its impact on health outcomes: a longitudinal study of patient portal use", *MIS Quarterly*, Vol. 44 No. 2, pp. 699-723.
- Bender-deMoll, S., Morris, M. and Moody, J. (2008), "Prototype packages for managing and animating longitudinal network data: dynamic network and rSoNIA", *Journal of Statistical Software*, Vol. 24 No. 7, pp. 1-36.
- Bhattacharjee, A. and Premkumar, G. (2004), "Understanding changes in belief and attitude toward information technology usage: a theoretical model and longitudinal test", *MIS Quarterly*, Vol. 28 No. 2, pp. 229-254.
- Buskens, V.W. (2002), *Social Networks and Trust*, Kluwer Academic Press, Dordrecht.
- Cooper, R.B. and Zmud, R. (1990), "Information technology implementation research: a technological diffusion approach", *Management Science*, Vol. 36 No. 2, pp. 123-139.
- Gersick, C.J.G. (1988), "Time and transition in work teams: toward a new model of group development", *Academy of Management Journal*, Vol. 31 No. 1, pp. 9-41.
- Ghose, A. and Todri-Adamopoulos, V. (2016), "Towards a digital attribution model: measuring the impact of display advertising on online consumer behavior", *MIS Quarterly*, Vol. 40 No. 4, pp. 889-910.
- Greenwood, B.N., Ganju, K.K. and Angst, C.M. (2019), "How does the implementation of enterprise information systems affect a professional's mobility? An empirical study", *Information Systems Research*, Vol. 30 No. 2, pp. 563-594.
- Hahn, J., Moon, Y.J. and Zhang, C. (2008), "Emergence of new project teams from open source software developer networks: impact of prior collaboration ties", *Information Systems Research*, Vol. 19 No. 3, pp. 369-391.
- Hall, E.T. (1983), *The Dance of Life: The Other Dimension of Time*, Doubleday, New York, New York.
- Havakhor, T. and Sabherwal, R. (2018), "Team processes in virtual knowledge teams: the effects of reputation signals and network density", *Journal of Management Information Systems*, Vol. 35 No. 1, pp. 266-318.
- Im, G. and Rai, A. (2014), "IT-enabled coordination for ambidextrous interorganizational relationships", *Information Systems Research*, Vol. 25 No. 1, pp. 72-92.
- Im, K.S., Grover, V. and Teng, J.T. (2013), "Do large firms become smaller by using information technology?", *Information Systems Research*, Vol. 24 No. 2, pp. 470-491.

-
- Jeyaraj, A. and Sabherwal, R. (2008), "Adoption of information systems innovations by individuals: a study of processes involving contextual, adopter, and influencer actions", *Information and Organization*, Vol. 18 No. 3, pp. 205-234.
- Johns, G. (2006), "The essential impact of context on organizational behavior", *Academy of Management Review*, Vol. 31 No. 2, pp. 386-408.
- Johns, G. (2018), "Advances in the treatment of context in organizational research", *Annual Review of Organizational Psychology and Organizational Behavior*, Vol. 5, pp. 21-46.
- Jones, J.M. (1988), "Cultural differences in temporal perspectives: instrumental and expressive behaviors in time", in McGrath, J. (Ed.), *The Social Psychology of Time: New Perspectives*, Sage Publications, Thousand Oaks, California, pp. 21-38.
- Kalish, Y., Luria, G., Toker, S. and Westman, M. (2015), "Till stress do us part: on the interplay between perceived stress and communication network dynamics", *Journal of Applied Psychology*, Vol. 100 No. 6, pp. 1737-1751.
- Kane, G.C., Alavi, M., Labianca, G. and Borgatti, S.P. (2014), "What's different about social media networks? A framework and research agenda", *MIS Quarterly*, Vol. 38 No. 1, pp. 275-304.
- Khan, Z. and Jarvenpaa, S.L. (2010), "Exploring temporal coordination of events with Facebook.com", *Journal of Information Technology*, Vol. 25 No. 2, pp. 137-151.
- Kim, Y., Jarvenpaa, S.L. and Gu, B. (2018), "External bridging and internal bonding: unlocking the generative resources of member time and attention spent in online communities", *MIS Quarterly*, Vol. 42 No. 1, pp. 265-283.
- Kohli, R. and Tan, S.S.L. (2016), "Electronic health records: how can IS researchers contribute to transforming healthcare?", *MIS Quarterly*, Vol. 40 No. 3, pp. 553-573.
- Langley, A. (1999), "Strategies for theorizing from process data", *Academy of Management Review*, Vol. 24 No. 4, pp. 691-710.
- Lawrence, P.R. and Lorsch, J.W. (1967), "Differentiation and integration in complex organizations", *Administrative Science Quarterly*, Vol. 12 No. 1, pp. 1-47.
- Levine, R.V. (1988), "The pace of life across cultures", in McGrath, J. (Ed.), *The Social Psychology of Time: New Perspectives*, Sage Publications, Newbury Park, California, pp. 39-60.
- Markus, M.L., Axline, S., Petrie, D. and Tanis, C. (2000), "Learning from adopters' experiences with ERP: problems encountered and success achieved", *Journal of Information Technology*, Vol. 15 No. 4, pp. 245-265.
- Markus, M.L. and Tanis, C. (2000), "The enterprise systems experience-from adoption to success", in Zmud, R. (Ed.), *Framing the Domains of IT Research: Glimpsing the Future through the Past*, Pinnaflex Educational Resources, Cincinnati, Ohio, pp. 173-207.
- McGrath, J. and Kelly, J.R. (1986), *Time and Human Interaction: Toward a Social Psychology of Time*, Sage Publications, New York, NY.
- Morris, M.G. and Venkatesh, V. (2010), "Job characteristics and job satisfaction: understanding the role of enterprise resource planning system implementation", *MIS Quarterly*, Vol. 34 No. 1, pp. 143-161.
- Mucha, P.J., Richardson, T., Macon, K., Porter, M.A. and Onnela, J.P. (2010), "Community structure in time-dependent, multiscale, and multiplex networks", *Science*, Vol. 328 No. 5980, pp. 876-878.
- Orlikowski, W.J. and Yates, J. (2002), "It's about time: temporal structuring in organizations", *Organization Science*, Vol. 13 No. 6, pp. 684-700.
- Perlow, L.A., Okhuysen, G.A. and Nelson, P.R. (2002), "The speed trap: exploring the relationship between decision making and temporal context", *Academy of Management Journal*, Vol. 45 No. 5, pp. 931-955.
- Poole, M.S. (2004), "Central issues in the study of change and innovation", in Poole, M.S. and Van de Ven, A.H. (Eds), *Handbook of Organizational Change and Innovation*, Oxford University Press, New York, NY, pp. 3-31.

- Poole, M.S. and Van de Ven, A.H. (1989), "Using paradox to build management and organization theories", *Academy of Management Review*, Vol. 14 No. 4, pp. 562-578.
- Poole, M.S. and Van de Ven, A.H. (2004), *Handbook of Organizational Change and Innovation*, Oxford University Press, New York, NY.
- Poole, M.S., Van de Ven, A.H., Dooley, K. and Holmes, M.E. (2000), *Organizational Change and Innovation Processes: Theory and Methods for Research*, Oxford University Press, Oxford.
- Putzke, J., Fischbach, K., Schoder, D. and Gloor, P.A. (2010), "The evolution of interaction networks in massively multiplayer online games", *Journal of the Association for Information Systems*, Vol. 11 No. 2, pp. 69-94.
- Real, K. and Poole, M.S. (2005), "Innovation implementation: conceptualization and measurement in organizational research", in Woodman, R. and Pasmore, W. (Eds), *Research in Organizational Change and Development*, Elsevier/JAI, Amsterdam, pp. 63-135.
- Ridings, C. and Wasko, M. (2010), "Online discussion group sustainability: investigating the interplay between structural dynamics and social dynamics over time", *Journal of the Association for Information Systems*, Vol. 11 No. 2, pp. 95-121.
- Riegelsberger, J., Sasse, M.A. and McCarthy, J. (2007), "Trust in mediated interactions", in Joinson, A.N., McKenna, K. and Postmes, T. (Eds), *The Oxford Handbook of Internet Psychology*, Oxford University Press, Oxford, pp. 53-69.
- Robert, L.P., Jr, Dennis, A.R. and Ahuja, M.K. (2008), "Social capital and knowledge integration in digitally enabled teams", *Information Systems Research*, Vol. 19 No. 3, pp. 314-334.
- Sabherwal, R. and Robey, D. (1995), "Reconciling variance and process strategies for studying information system development", *Information Systems Research*, Vol. 6 No. 4, pp. 303-327.
- Sasidharan, S., Santhanam, R., Brass, D.J. and Sambamurthy, V. (2012), "The effects of social network structure on enterprise systems success: a longitudinal multilevel analysis", *Information Systems Research*, Vol. 23 No. 3, pp. 658-678.
- Snijders, T.A.B., van de Bunt, G.G. and Steglich, C.E.G. (2010), "Introduction to stochastic actor-based models for network dynamics", *Social Networks*, Vol. 32, pp. 44-60.
- Sykes, T.A. (2015), "Support structures and their impacts on employee outcomes: a longitudinal field study of an enterprise system implementation", *MIS Quarterly*, Vol. 39 No. 2, pp. 473-495.
- Sykes, T.A. "Enterprise system implementation and employee job outcomes: understanding the role of formal and informal support structures using the job strain model", *MIS Quarterly*, forthcoming.
- Sykes, T.A. and Venkatesh, V. (2017), "Explaining post-implementation employee system use and job performance: impacts of the content and source of social network ties", *MIS Quarterly*, Vol. 41 No. 3, pp. 917-936.
- Sykes, T.A., Venkatesh, V. and Gosain, S. (2009), "Model of acceptance with peer support: a social network perspective to understand employees' system use", *MIS Quarterly*, Vol. 33 No. 2, pp. 371-393.
- Thompson, S., Whitaker, J., Kohli, R. and Jones, C. (2020), "Chronic disease management: how IT and analytics create healthcare value through the temporal displacement of care", *MIS Quarterly*, Vol. 44 No. 1-b, pp. 227-256.
- Trier, M. (2008), "Towards dynamic visualization for understanding evolution of digital communication networks", *Information Systems Research*, Vol. 19 No. 3, pp. 335-350.
- van Emmerik, H. and Sanders, K. (2004), "Social embeddedness and job performance of tenured and non-tenured professionals", *Human Resource Management Journal*, Vol. 14 No. 1, pp. 40-54.
- Venkatesh, V., Brown, S.A., Maruping, L.M. and Bala, H. (2008), "Predicting different conceptualizations of system use: the competing roles of behavioral intention, facilitating conditions, and behavioral expectation", *MIS Quarterly*, Vol. 32 No. 3, pp. 483-502.

-
- Venkatesh, V., Maruping, L.M. and Brown, S.A. (2006), "Role of Time in Self-prediction of Behavior", *Organizational Behavior and Human Decision Processes*, Vol. 100 No. 2, pp. 160-176.
- Venkatesh, V., Morris, M., Davis, G. and Davis, F. (2003), "User acceptance of information technology: toward a unified view", *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478.
- Venkatesh, V., Rai, A., Sykes, T.A. and Aljafari, R. (2016), "Combating infant mortality in rural India: evidence from a field study of eHealth kiosk implementations", *MIS Quarterly*, Vol. 40 No. 2, pp. 353-380.
- Venkatesh, V., Sykes, T.A. and Zhang, X. (2020), "ICT for development in rural India: a longitudinal study of women's health outcomes", *MIS Quarterly*, Vol. 44 No. 2, pp. 605-629.
- Venkatesh, V., Thong, J.Y.L. and Xu, X. (2012), "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology", *MIS Quarterly*, Vol. 36 No. 1, pp. 157-178.
- Venkatesh, V., Zhang, X. and Sykes, T.A. (2011), "'Doctors do too little technology': a longitudinal field study of an electronic healthcare system implementation", *Information Systems Research*, Vol. 22 No. 3, pp. 523-546.
- Waller, M.J., Conte, J.M., Gibson, C.B. and Mason, A.C. (2001), "The effect of individual perceptions of deadlines on team performance", *Academy of Management Review*, Vol. 26 No. 4, pp. 586-600.
- Yakura, E.K. (2002), "Charting time: timelines as temporal boundary objects", *Academy of Management Review*, Vol. 45 No. 5, pp. 956-970.
- Yan, L. and Tan, Y. (2017), "The consensus effect in online health-care communities", *Journal of Management Information Systems*, Vol. 34 No. 1, pp. 11-39.
- Zaheer, S., Albert, S. and Zaheer, A. (1999), "Time scales and organizational theory", *Academy of Management Review*, Vol. 24 No. 4, pp. 725-741.
- Zhu, K., Kraemer, K.L., Gurbaxani, V. and Xu, S. (2006a), "Migration to open-standard interorganizational systems: network effects, switching costs, and path dependency", special issue, *MIS Quarterly*, Vol. 30, pp. 515-539.
- Zhu, K., Kraemer, K.L. and Xu, S. (2006b), "The process of innovation assimilation by firms in different countries: a technology diffusion perspective on e-business", *Management Science*, Vol. 52 No. 10, pp. 1557-1576.

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