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OFFERING ACCOUNTS OF COMPLEX IS-PHENOMENA: TOWARDS A COMBINATION OF MECHANISTIC PREDICTIONS AND GENERATIVE EXPLANATIONS

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Abstract

Information Systems (IS) phenomena have become increasingly volatile, complex and fast changing. Capturing their essence is an increasingly daunting task. Data science have emerged in awe to predict future outcomes. Decision-making thus becomes faster while data become bigger. Yet, in the wake of this promising path, many of these predictions lack accuracy due to the unpredictability of complex phenomena. That is why researchers promote the importance of thick qualitative data analysis as a way of seeking explanations of the generativity underlying complex phenomena. This approach is (in comparison) slow, but can answer why events occurred. Thus, we argue that sound accounts of complex IS-phenomena must come from a combinatory approach of fast predictions with slower accounts. Predictions apply laws theorized as causal mechanisms. When these outcomes do not arise, we suggest applying explanatory accounts that apply a different form of causality - generative mechanisms. Generative mechanisms can explain unpredictable outcomes, but can only be inferred through longitudinal qualitative studies. This paper opens up a research agenda for combinatory approaches of fast mechanistic predictions from big data and slower generative explanations from thick data. This combination will help capturing the essence of complex socio-technical phenomena in our capricious digitalized world.

Keywords: Big data, Thick data, Explanation, Predictions, Generative Mechanisms, Causal Mechanisms

1 Introduction

We live in an era where decision making are increasingly based on data points from humans' behavior aggregated into big data sets (Abbasi, Sarker and Chiang, 2016; Agarwal and Dahr, 2014; McAfee and Brynjolfson, 2012). In the wake of big data, data science has emerged as a discipline. Data Science is a profession and a research agenda where the goal is to build systems and algorithms to extract knowledge, find patterns, generate insights and make predictions from diverse data for various applications and visualization[1]. The impact on decisions and actions are profound and data-driven decision-making is increasingly used by executives, managers and employees (Henke et al, 2017; Abbasi, Sarker and Chiang, 2016; Madsbjerg and Rasmussen, 2014). In the wake of this development, a prevailing position seems to be that if we can predict human behavior and account for what can and will happen, we do not need to understand or explain how and why it happened (Shmueli and Koppius, 2011; Agarwal and Dhar, 2014; Vuthar, 2018). The current stance taken by big data enthusiasts seem to be that it is possible to actually create accurate models predicting outcomes, such as spread of ideas in an online realm.

[1] https://dsr.cise.ufl.edu/

However, these models fail "to predict the behavior change produced by this very same campaign" (Cebrian et al., 2016). We tend to rely more and more on predictive analytics to deliver causal accounts.

Data science is a much faster way of getting access to insight on future human behaviors than the slower process of longitudinal qualitative inquiries (Agarwal and Dhar, 2014). However, these different approaches are geared towards two different knowledge outcomes. Data science produces nomothetic knowledge by building on and deriving causal laws that explain types or categories of objective phenomena (Cone, 1989). These insights inform future behaviors inferred from mechanistic predictions. Thus, data science gives prominence to the *what* without the *why* (Abbasi, Sarker and Chiang, 2016). Idiographic methods, on the other hand, are geared toward generative explanations to why and how phenomena came to be (Smuelli and Koppius, 2011; Cone, 1989).

In parallel with the evolution of data-science, big data and predictive analytics, the phenomena we study in IS have become increasingly complex, volatile and unpredictable (Ang, 2011; Grover and Lyytinen, 2015). Researchers increasingly account for complex phenomena by using social mechanisms as theoretical devices (Avgerou, 2013; Archer, 2015; Mingers and Standing, 2017). While some quantitative researchers have turned to big data for answers through causal mechanisms (Abbasi, Sarker and Chiang, 2016) others more qualitative researchers have used critical realism to find generative mechanisms in thick data (Volkoff and Strong, 2012; Henfridsson and Bygstad, 2013; Mingers and Standing, 2017). Causal and generative mechanisms are the two faces of social mechanisms. We suggest a combinatorial approach, that on the one hand, carries rich inquiries using innovative and extensive data sets and, and on the other hand, generates novel, genuine, high-level theorizing around connected conceptual relationships between IT, information and its representations and social behaviors (Grover and Lyytinen, 2015). Rigorous and relevant accounts of complex IS-phenomena cannot be obtained using one or the other approach alone. Thus, we ask: *"How can big and thick data approaches be combined and balanced through the lens of social mechanisms to improve predictions and explanations of complex IS-phenomena?"*

The purpose of this research-in-progress is to heighten awareness of combining accounts that can explain and predict outcome patterns in complex IS-phenomena from empirical data. While data science gives prominence to predictive mechanistic claims, we claim that generative explanations are superior when explaining complex relationships; and why they enforce, halt and produce a certain outcome. The former approach addresses *what-questions* in which mechanistic social mechanisms clarify the causal relationship between an antecedent and an outcome. The latter approach addresses the *how and why questions* in which generative social mechanisms arise as key explanatory tools to look at the sequence of events or process leading to the outcome. The second purpose of this paper is to bring forward a research agenda that promotes an elaborated understanding of the power of social mechanisms both mechanistic and generative. A combinatory approach provide IS-researchers and decision makers with a better approach to addressing accurately what, how and why certain socio-technical events occur.
The paper is organized as follows. In section 2, we give a brief description of social mechanisms and how they are used to both predict and explain phenomena. In section 3, we illustrate combinations of explanations and predictions through empirical vignettes. Finally, we discuss the proposed framework as the starting point of our future research.

2 Mechanisms as accounts of what, why and how

According to Hedström and Ylikoski (2010), researchers explain an observed outcome by referring to social mechanisms. According to Pawson (2008) mechanisms are theoretical tools that have the valuable property of abstraction. They have the power of conceptual abstraction that provides the necessary device to allow research to transfer, test and shape the same explanatory ideas in different domains and contexts. In IS-Research, several social mechanisms account for outcomes from the introduction of technical artefacts into a social world. An example is the institutionalization mechanism explaining the sequence of how a task, formerly done by an individual, is transformed into an IT-artefact that is used in concert by a group sharing the same tasks (Ropohl, 1999). Social mechanisms thus strengthen the explanatory capacity of IS-research of a phenomenon happening (*what)* (Avgerou, 2013) by tracing the sequence of mechanisms that bring about IS phenomena (*how and why)* (Bygstad, Munkvold and Volkoff, 2016).

Social mechanisms are small pieces of theories that can account for things happening in the sense that they explain "the cause of something"; and what 'enables' or 'leads to' a certain event" (Sayer, 1992, p.104.). A mechanism, thus, refers to a constellation of entities and activities that are organized such that they regularly bring about a particular type of outcome. IS-researchers have lately promoted social mechanisms as important to theorizing complex IS-phenomena (Avgerou, 2013; Henfridsson and Bygstad, 2013; Bygstad, Munkvold and Volkoff, 2016; Mingers and Standing, 2017; Markus and Rowe, 2018). Asking not just what, but also why certain IS-phenomena came to be, and thus how they occur, is a core research activity. An understanding of the nature of causality becomes a prerequisite for the conduct of the research (Pawson, 2008; Avgerou, 2013).

Causation refers to something happening in the real world, that is, a process that connects inputs to outputs, such as a transfer of matter, energy, or information or a human or social dynamic, such as the self-fulfilling prophecy (Markus and Rowe, 2018). There are different types of accounts made within causation. To simplify our argument, we present two types of social mechanisms: causal mechanisms and generative mechanisms (Table 1). Both are used in accounts of IS-phenomena. Causal mechanisms refer to the successionist and mechanistic account of X always causing Y (causal laws); and the configurational account in which the particular configuration of attributes within a system, provides the trigger for system transformation and thus, the consequences (Pawson, 2008). Generative mechanisms aim at identifying the sequence of events that led to an outcome or the absence of outcome (causal potentials) (Bygstad, Munkvold and Voloff, 2016). Generative mechanisms are quite different to such an extent that they defy a simple, unitary definition of their nature and content (Archer, 2015; Pawson, 2008).

	Causal Mechanisms	Generative mechanisms
Usage	To predict what will happen (outcomes) in a mechanistic way.	To explain the process of generative change from historical accounts of how and why an outcome happened.
Answers	What?	Why and how?
Focus	Antecedents, outcomes and future change	Change process, sequence of events from past
Epistemology	Naturalism	Positivist
Ontology	Objectivism	Interpretivist/moderate constructivism
Knowledge	Nomothetic	Ideographic
Causality	Causal laws	Causal potentials
Examples	An example in IS-Research is the immediate nomological net of how an IT-artefact, its usage and impact in an organization, influence IT-management practices and capabilities (Benbasat & Zmud, 2003). The elements of a nomological net has at least two constructs, a theoretical proposition, construct that can be measured, operational and linked through	An example in IS-Research is from Henfridsson and Bygstad (2013). They identify three generative mechanisms of digital infrastructure: innovation, adoption, scaling and how they contingently lead to evolution outcomes. Second, they use these mechanisms as a basis for developing a configurational perspective that advances current knowledge about why some digital infrastructures evolve successfully while

	hypotheses before data collection. Empirical generalization after data collection.	others do not. These evolutions processes must be inferred from empirical qualitative data
Method of science	Through Hypothesis Testing Patterns and relationships are spotted by algorithms and generate theories of the future.	Through Retroduction and Retrodiction. Retroduction is to discover the interacting mechanisms and structures that generate a phenomenon. Retrodiction starts from the envisioned mechanisms that have already been hypothesized and supported by previous research.

Table 1. Social Mechanisms

We seek to deliver an approach that can explain *why* complex IS-phenomena occur, and inform the inaccuracy of the mechanistic predictions from big data, leading to more rigorous accounts and better predictions. We suggest an approach that uses retroduction and retrodicition as modes of inference of mechanisms, recently re-theorized by McAvoy and Butler (2017).

3 The power of combining explanations and predictions

In this section, we aim at illustrating through two vignettes the complementarity of causal and generative mechanisms. While research has focused on deriving causal laws, we focus on explaining how to derive causal potentials. First, in vignette 1, we give an example of how generative mechanisms were identified in a techno- organizational context in which the causal mechanism of institutionalization triggered by new technology no longer fully explained the behavior outcomes. We used retroduction to derive the generative mechanisms. We combined it with retrodiction, by finding theoretical support of the existence of such generative mechanisms. This vignette supports our claim of generative mechanisms being superior in explaining complex IS-phenomena. It also explains how an understanding of generative mechanisms informs which future outcomes to expect when new technologies are introduced in an organizational context. Second, in vignette 2, we illustrate of how predictions from big data are used in large scale phenomena and how the causal mechanisms embedded in the predictions fail in predicting the right outcome. In the 2016 Presidential run, all the major polls were misled in giving Hillary Clinton the win. We argue that big data alone cannot produce accurate pictures of what will happen. Nowadays, access to the data is not a problem. Yet, processing it remains a struggle when algorithms neglect nuances and context. This vignette supports our claim of generative mechanisms being superior in explaining IS-phenomena.

3.1 Vignette 1 - Digital Workplace studies in a socio-technical perspective

The socio-technical perspective is often used to explain how technology and social elements within the workplace interacts and relates. The perspective focuses on groups sharing the same task, technology and working conditions. It is assumed that a harmonized work system emerges from the interaction between the same technology, behaviors and social norms (Sarker, Chatterjee and Xiao, 2010). However, harmony rarely surface in the contemporary workplace, even though digital workplace theories anticipate harmonized outcomes caused by social mechanisms of institutionalization and socialization (Ropohl, 1999). A longitudinal qualitative study of digital workplace behaviors carried out from 2016-2018 involving 49 individual knowledge professionals in digital global work-settings revealed that other social mechanisms were activated. The outcomes from usage of Unified Communication and Collaboration technology rarely resulted in institutionalized ways of working, socialized behaviors and shared routines. The usual socio-technical explanation on how organizations change due to technology implementation, no longer covered the dynamic nature in knowledge work-settings (Fischer and Baskerville, forthcoming). In particular, the entrance of Social, Mobile and Cloud technology enabled much more individualized work-patterns in which the individual increasingly took control of time, pace, place, information flows and social relationships. The stability from deep structures and organizational routines were challenged from non-routine work carried out in fluid and fast changing networks and through individually variable routines at the surface level (Fischer and Baskerville, 2018). Thus, arriving at harmony and fit were increasingly difficult. Observed outcomes were either rigid socio-technical arrangements or uncoordinated individualized practices. How to achieve economic and human objectives had become much more complicated (Fischer and Baskerville, forthcoming). The cases were analyzed using a critical realist analysis method with a focus on affordances (Bygstad, Munkvold and Volkoff, 2016). Singling out affordances from two different kinds of IT-artefacts: the malleable-individual, and the fixed-organizational, the study could now explain outcomes from an upper-level generative mechanism of individualization-socialization, changing the balance in the socio-technical system in profounds ways (Fischer and Baskerville, 2018b). The analysis gave a more rigorous explanatory account of how generative mechanisms operate as continuum and cause various outcome patterns. The generative mechanism explained how the nexus between technology, the social world and individual actions arrived at different outcomes of productive workplace behaviors.

To conclude on vignette 1, the outcome of the research were candidate generative mechanisms that combine in unpredictable ways in the digital global workplace. This is the process of retroduction of generative mechanisms conjectured from longitudinal empirical investigations. Moving forward, we found support of the mechanisms in the field of sociology. This is the process of retrodiction.

3.2 Vignette 2 - 2016 US Presidential Elections: A polling prediction failure?

Not only industries but also politics have turned to data science. This raises new expectations and challenges when it comes to voting behavior. We focus on the 2016 US Presidential Elections has been described as an epic polling failure for data scientists. Most of the political polls failed to predict the outcomes (Lohr & Singer, 2016). Pollsters and statisticians gave Hillary Clinton winning the elections with a probability between 75% and 99% (Tamman and Faulconbridge, 2016). This outcome results from multiple interacting mechanisms.

The mechanisms are not mutually exclusive. Statisticians and pollsters have applied their working assumptions about voters based on historical voting patterns that were supported, i.e. they retrodiced. Their flawed assumptions underestimated the support for Trump. The mechanistic causal nature of polling behavior models did not predict the actual outcome. We try to trace back the mix of causal mechanisms that interacted and produced unexpected outcomes, i.e. we retroduce.

One way to retroduce and complement predictive analytics is to conduct a multi-case approach such as McAvoy and Butler (2017) recommend. When we compare elections outcomes and polls from 2012 and 2016. Obama’s and Clinton’s situations were different on two dimensions (Silver, 2017): polls were giving Obama’s stronger weight in swing states and undecided voters represented a larger population in 2012. These elements are important to identify mechanisms. Most importantly, they explained how we do not observe the predicted outcome but the actual observed outcome. The models were not refined as the world changed and thus, models have lost in predictive power over time.

Another way is to adopt a longitudinal approach and follow the same voters across elections. This approach is valuable because it reveals that predictive models were based on demographics when psychological behaviors played a critical role in voting behavior. Such approach enables to build portraits of voters over time instead of snapshots.

The identified mechanisms are physical and social (Mingers, 2000). The physical attributes of an election are the popular vote and the Electoral College. Yet, the popular vote cannot predict the Electoral College outcome, needed to win the election. Therefore, while popular vote polling were relatively accurate, the importance of big states in the outcome was overstated. Social attributes were also at play as the polls missed two categories of voters: the undecided and the first-time voters. What some called the “shy Trump” effect (Cohn, 2017), i.e. the secret Trump voters who were not vocal about their political ideas because of social shaming, was invisible in polling. Moreover, following a post-election polling (Kennedy et al., 2017), undecided voters or people who did not think that their vote mattered turned out to massively vote for Trump.

To conclude on vignette 2, these mechanisms are retroduced from empirical data and should be considered as alternative explanations to be studied in other contexts. Further research needs to investigate if these mechanisms are really at play, refine them and complete them if necessary to build a causal framework. Therefore, from these preliminary findings, we need to use retrodiction.

4 Discussion

Figure 1 represents the point of departure of the discussion and future research. It illustrates the differences between the two approaches and is our initial framework at this early stage of our research. It attempts to reconcile the dichotomy and combine the two approaches as asked for in the research question. In conceptualizing the double-loop (Figure 1), we were inspired by Müller, Mathiassen and Saunders (Forthcoming) who call for pluralist theory building and Mingers' (2001) call for pluralism. While Müller et al. (forthcoming) call for pluralism in theory use to advance knowledge, Mingers (2001) calls for methodological pluralism. To account for complex IS-phenomena (at the center of the Figure 1), we adopt their insights on pluralism in developing causality. It implies both pluralistic views. On the one hand, we have a pluralistic approach with mechanisms as pieces of theory. On the other hand, we have a pluralistic approach of research methodology with predictive analytics and in-depth qualitative research.

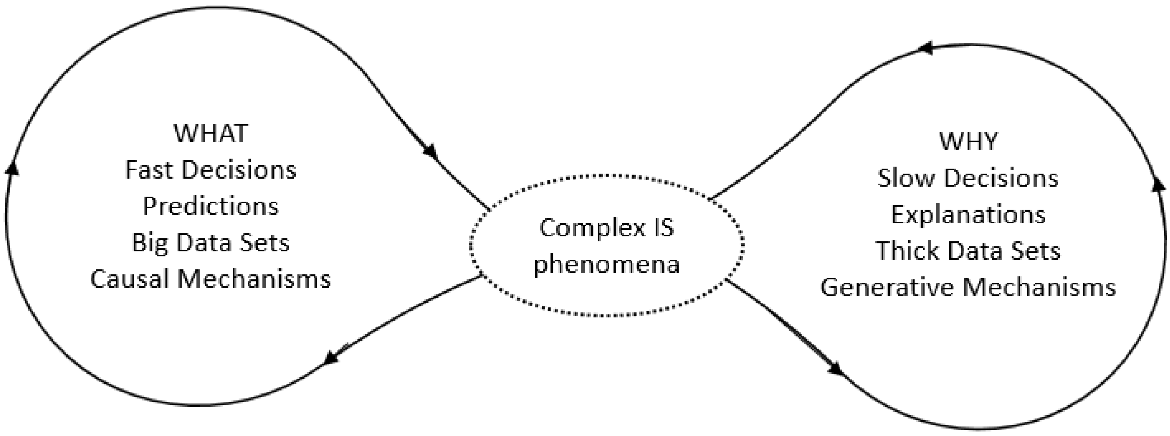

Figure 1. The combinatory approach to accuracy in accounts of complex IS-phenomena

The *"what"* loop is research that answers *what happened and what will happen* in the future. It is based on theories that rely on causal mechanisms. The theoretical causality is inherent in the algorithms predicting the most likely outcome. This approach delivers fast predictions based on algorithms that are basically a set of rules that precisely defines a sequence of operations and thus, delivers an outcome based on the theory of causality between X and Y. We suggest a retrodictive approach to uncover the causal mechanisms underlying the predictions. This will illuminate how the predictive model predicted that specific outcome. However, as we have argued, this does not reveal the generative dynamics pertaining to the context. As we have shown in vignette 2, predictions are not accurate. They are blind to other generative mechanisms that can influence the outcome. Answering *why* something occurred is not possible in the first approach. Thus, carrying out the second loop is necessary.

The *"why"* loop is research *answering why and how* an outcome occurs. These studies are based on thick data that are derived from longitudinal qualitative studies. We call it slow research. In the critical realist position, phenomena are always caused by a specific combination of generative mechanisms that are triggered, and cause an outcome. These generative mechanisms span a continuum that can explain *the why*. Vignette 1 showed the explainable powers of generative mechanisms. Often the approach is based on retroduction first, and then retroduction. The outcomes are rigorous descriptions of generative mechanisms that can explain other complex IS-phenomena.

We discuss our suggested approach around a proposed research agenda that can provide more accuracy and a balance between fast and slow decisions

The goal of the research is to offer a framework that combines big and thick data for both practical and academic reasons. While a plethora of data are available to us, a major concern about our ability to leverage these data in accurate and reliable models remains. Our global, political, economic environment stability is challenged and challenges the sustainability of our models. This challenge underlies the modelling exercise to which many IS-researchers contribute. We witness our societies evolving sometimes discreetly, sometimes creating social unrest. However, they evolve rapidly. Nowadays, we face “wicked problems” (Churchman, 1967). These problems are wicked because they have unintended consequences and they can be called problems because we cannot formulate a stable problem statement. Therefore, to build better models and be able to predict what is going to happen next, we need to better comprehend what these social evolutions means and why they occur. This can provide more accuracy. Humans are attracted to fast decisions (Kahneman, 2012). This inclination is enabled enormously by the advent of usage and accessibility of big data sets of human behavior and the predictive analytical models that can be applied to this information. However, researchers must be able to answer the question how and why, in order to explain thoroughly why certain events occur. This implies not only slow and longitudinal research, but also involves slow thinking to provide rigorous answers (Kahneman, 2012). We contribute to the discussion propelled by Grover and Lyytinen (2015) on *how to* combine inquiries using innovative and extensive data sets and, theorize novel high-level explanation of conceptual relationships between IT, information and social behaviors (Grover and Lyytinen, 2015). Our proposed framework can contribute with a way forward.

We propose a double-loop between retroduction and retrodiction. These two modes of explanations can be perceived as a sequence. Then, may arise a chicken-and-egg problem: which comes first? For widely studied topics in our discipline, we never start in ignorance. We use previous experience, previous work and published results from our peers. Therefore, we start with retroduction. Yet, at that stage, the trap is to take our assumptions for granted about the kind of causal mechanisms existing and activated to explain a social phenomenon. Unchallenged ontology assumptions that have been supported in specific context may vary across place and time. While “standing on the shoulders of giants” is relying on already analyzed experiences, sometimes, distorted ontological assumptions or researchers’ own bias jeopardize the accuracy of our predictions. Retrodiction without retroduction takes the risk to rely on faulty assumptions that do not account for context, nor nuances. These assumptions being used to write algorithms, they need to be supported by empirical evidence and have boundary conditions to theorize how the causal mechanisms interact and operate. The reverse also holds its share of risks. Retroduction without retrodiction involves epistemological assumptions, i.e. how causal and generative mechanisms are derived from empirical observations. Thus, retroduction without retrodiction may involve ecological fallacy. Our framework contributes to combining the two.

We contribute to the discussion of social mechanisms in IS-research and draw attention to generative explanations of mechanisms as explanatory accounts. It resides in the realm of critical realism that is a philosophy and a method (Mingers, 2000; Wynn and Williams, 2012; Williams and Karahanna, 2013; Henfridsson and Bygstad, 2013; Mingers and Standing, 2017). Our research-in-progress reasserts the relevance of a critical realist approach for current IS challenges. Furthermore, we argue for the formulation of generative mechanisms to advance theorization. To do so, we have specified the importance and articulation of inference modes for IS researchers’ objects of interests. Retroduction and retrodiction inferences (McAvoy & Butler, 2017) are part of an iterative reasoning to complement rigorous analytics research that builds on combination of fast mechanistic predictions and slow generative explanations.

5 Next Steps

To develop and evaluate the framework, we need deeper engagement with a plethora of cases involving volatile, complex and elusive IS-phenomena. Cases from big data and from longitudinal studies must be scrutinized, to further develop the frameworks accuracy. Each concept, arrow and categorization will be questioned in figure 1. We will investigate the value of explaining the *why*, while having fast access to the *what.* This could improve theory building. However, we will also seek to deliver value to practitioners and managers, in decision-making and hypothesis building. This is the paramount aim of this research. We will offer an approach to acknowledge the strengths from both approaches towards more accurate explanations that can benefit both researchers and practitioners.

References

Abbasi, A. Sarker, S. & Chiang, R. H. L. (2016). Editorial: Big Data Research in Information Systems: Toward an Inclusive Research Agenda. *Journal of the Association for Information Systems* 17(2), pp. i – xxxii

Archer, M.M. (2015). *Generative Mechanisms Transforming the Social Order*. Springer International Publishing, Switzerland.

Agarwal, R., & Dhar, V. (2014). Editorial: "Big data, data science, and analytics: The opportunity and challenge for IS research." *Information Systems Research* 25(3), pp. 443-448

Ang, I. (2011). "Navigating complexity: From cultural critique to cultural intelligence." *Continuum* 25(6), pp 779-794.

Avgerou, C. (2013). "Social Mechanisms for Causal Explanation in Social Theory Based IS Research." *Journal of the Association for Information Systems* 14(8), pp 399- 419.

Benbasat, I., & Zmud, R. W. (2003). "The Identity Crisis Within the IS Discipline: Defining and Communicating the Discipline's Core Properties." *MIS Quarterly* 27 (2)

Bygstad, B. Munkvold, B. & O. Volkoff, (2016). "Identifying generative mechanisms." *Journal of Information Technology* 31 pp. 83–96.

Cebrian, M., Rahwan, I. & Pentland, A. S. (2016)." Beyond viral." *Communications of the ACM* 59(4), pp 36-39.

Churchman, C. W. (1967). Guest Editorial "Wicked problems." *Management Science* 14(4) pp. B141-B142

Cohn, N. (2017). "A 2016 Review: Why Key State Polls Were Wrong About Trump." [Online]. *The New York Times*, May 31 2017. Available: https://www.nytimes.com/2017/05/31/upshot/a-2016-review-why-key-state-polls-were-wrong-about-trump.html. Last Access on Nov. 27 2018

Cone, J. D. (1986). "Idiographic, nomothetic, and related perspectives in behavioral assessment." In: R. O. Nelson & S. C. Hayes (eds.): *Conceptual foundations of behavioral assessment* (pp. 111–128). New York: Guilford.

Fischer, L.H. & Baskerville, R. (Forthcoming). "Revising the socio-technical perspective for the 21st century: New mechanisms at work." *International Journal of Social and Organizational Dynamic and Information Technology*

Fischer, L.H. & Baskerville, R. (2018). "Socio-technical Change: The Equilibrium Paradox." *ECIS 2018 Proceedings*, Portsmouth

Grover, V. & Lyytinen, K. (2015). "New State of Play in Information Systems Research: The Push to the Edges." *MIS Quarterly* 39(2), pp 271-296.

Hedström, P. & Ylikoski, P. (2010). "Causal mechanisms in the social sciences." *Annual review of sociology* 36(1), pp 49-67.

Henfridsson, O. & Bygstad, B. (2013). "The Generative Mechanisms of Digital Infrastructure Evolution." *MIS Quarterly* 37(3), pp 907-931.

Henke, N, Bughin, J. Chui, M. Manyika, J. Saleh, T, Wiseman, B., Sethupathy, T.G. (2016). "The age of analytics: competing in a data-driven world." [Online]. Mckinsey Global Institute 2016. Available: https://www.mckinsey.com/~/media/mckinsey/business%20functions/mckinsey%20analytics/our%

20insights/the%20age%20of%20analytics%20competing%20in%20a%20data%20driven%20world/mgi-the-age-of-analytics-full-report.ashx. Last Access on Nov. 27 2018

Kahneman, D. (2012). *Thinking, fast and slow*. Penguin Books

Kennedy, C., Keeter, S., Mercer, A., Hatley, N., Bertoni, N. & Lau, A. (2017) "Are Telephone Polls Understating Support for Trump?" [Online] Pew Research Center, Available: https://www.pewresearch.org/methods/2017/03/31/are-telephone-polls-understating-support-for-trump/ Last Access on Nov. 27 2018

Lohr, S. & Singer, N. (2016). "How Data Failed Us in Calling an Election." [Online]. *The New York Times*, Nov. 10, 2016. Available: https://www.nytimes.com/2016/11/10/technology/the-data-said-clinton-would-win-why-you-shouldnt-have-believed-it.html. Last Access on Nov. 27 2018.

Madsbjerg, C. & Rasmussen, M. (2014). *The moment of clarity: using the human sciences to solve your toughest business problems*. Harvard Business Review Press.

Markus, M. L. & Rowe, F. (2018). "Is IT changing the world? Conceptions of causality for information systems theorizing." *MIS Quarterly* 42(4), pp 1255 - 1280.

McAfee, A., & Brynjolfsson, E. (2012). "Big data: The management revolution." *Harvard Business Review*. [Online] Available: https://hbr.org/2012/10/big-data-the-management-revolution/ar Last Access on Nov. 27 2018

McAvoy, J. & Butler, T. (2017). "Causal Framework Through Retroduction And Retrodiction." *ECIS 2017 proceedings*, Guimarães

Mingers, J. (2000). "The contribution of critical realism as an underpinning philosophy for OR/MS and systems." *Journal of the Operational Research Society* 51(11), pp 1256-1270.

Mingers, J., & Standing, C. (2017). "Why things happen–Developing the critical realist view of causal mechanisms." *Information and Organization* 27(3), pp. 171-189.

Müller, S. D., Mathiassen, L., & Saunders, C. (Forthcoming). "Pluralist Theory Building: A Methodology for Generalizing from Data to Theory." *Journal of the Association for Information Systems*

Pawson, R. (2008). "Causality for beginners." NCRM Research Methods Festival 2008 (non-published). Available: http://eprints.ncrm.ac.uk/245/ Last Access on March, 29, 2019

Ropohl, G. (1999). "Philosophy of socio-technical systems." *Society for Philosophy and Technology* 4 (3)

Sarker, S., Chatterjee, S., & Xiao, X. (2013). "How "Sociotechnical" is our IS Research? An Assessment and Possible Ways Forward". *ICIS 2013 Proceedings*, Milan

Silver, N. (2017). "The Invisible Undecided Voter." [Online] FiveThirtyEight. Available: https://fivethirtyeight.com/features/the-invisible-undecided-voter/. Last Access on March, 29, 2019

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

Tamman, M. & Faulconbridge, G. (2016). "How the polls, including ours, missed Trump's victory." [Online] Reuters, November, 9 2016. Available: https://www.reuters.com/article/us-usa-election-polls/how-the-polls-including-ours-missed-trumps-victory-idUSKBN1343O6 Last Access on March, 29, 2019

Volkoff, O. & Strong, D.M. (2013). "Critical Realism and Affordances: Theorizing IT-Associated Organizational Change Processes." *MIS Quarterly* 37(3) pp. 819-834.

Vuthar, A. (2018). "Could machine learning mean the end of understanding in science?" [Online]. Available: https://theconversation.com/could-machine-learning-mean-the-end-of-understanding-in-science-98995. Last Access on March, 29, 2019

Williams, C. K. & Karahanna, E. (2013). Causal Explanation in the Coordinating Process: A Critical Realist Case Study of Federated IT Governance Structures. *MIS Quarterly* 37(3), pp 933-964.

Wynn, D., Jr. & Williams, C. K. (2012). "Principles for conducting critical realist case study research in information systems." *MIS quarterly* 36(3), pp 787-810.