EDITOR'S COMMENTS

Commonalities Across IS Silos and *Intra*disciplinary Information Systems Research

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In my first editorial, I listed promoting *intra*disciplinary IS research as one of the goals I would like to pursue for *MISQ*. As opposed to the more common interdisciplinary and multidisciplinary counterparts, the term *intradisciplinary* is seldom used. So, what does it mean? In the context of IS, it refers to combining different IS research streams, methods or methodologies, which are typically employed separately within the discipline, into unified efforts to tackle research problems.

In this editorial, I present loosely connected thoughts about two inter-related ideas that are dear to me: (1) despite inherent divisions in the way we think about IS research, there are various commonalities in our approaches; we are closer in research principles and execution than one may think, and (2) at the current juncture, there is a lot to gain from weaving our approaches together to tackle impactful research.

The way our discipline evolved over the last 40+ years generated solid but independent "silos" of research streams. Behavioral IS research, organizational IS research, information systems economics, and design science are generally recognized as prevalent streams and paradigms. With rare exceptions, different IS departments and faculty around the country also organize themselves and their graduate programs following this divided structure. This is not surprising because in a doctoral program it is natural to favor depth over breadth. As a result, graduate students are often trained well in one of the streams but lack the perspective of the other IS approaches. My own research trajectory exemplifies this situation. My Ph.D. program in Rochester stressed analytical modeling and economics as methodological foundations and what is now known as design science and economics of IS as research paradigms. In my doctoral formation years, I had no exposure to other views of IS research. I know of several IS researchers who have had a similar experience: growing up as researcher in one environment with limited or no exposure to other research paradigms and their associated methods.

Each one of these well recognized streams builds on its own reference disciplines. Within each stream, there are sub-streams, with competing methods, approaches, paradigms, and methodologies. For example, economics of IS is typically divided between analytical modeling and econometrics. Behavioral IS research can follow a qualitative or a quantitative approach, can prescribe to positivism or interpretivism, and so on and so forth. Within each stream, camps and sub-camps abound in the IS academic world with their own workshops, preferred conferences, and editorial appointments in the journals. I do believe that due to the nature of the field and the phenomena of interest we choose to study, having this multi-pluralism of paradigms, methods, and methodologies is necessary and healthy.

The questions that arise are, can they coexist in the same research project and why would we want to do it? Without going into the semantic differences between multimethod research and mixed-method research (Venkatesh et al. 2013), over the years authors have argued for intradisciplinary methods to research, especially within the paradigms of behavioral and organizational research. See, for example, Orlikowski and Baroudi (1991), Mingers (2001), and the recent work by Venkatesh et al. (2013). But the reality is that in practice very few IS works take a pluralist approach. This is confirmed by Venkatesh et al., who undertook a thorough review of articles published in the six journals of the AIS Senior Scholars basket (AIS 2007) and found that less than 5 percent of all the articles published between 2001 and 2007 could be considered in this category.

The reasons for the scarcity of intradisciplinary work in the discipline are easy to identify:

(1) We are not trained to do it. Researchers in one stream or sub-stream don't typically embrace approaches of another stream or sub-stream. Bridging the gap may be too difficult.

(2) Our academic institutions don't provide the incentives for this cross-pollination of ideas.

(3) Guidelines for doing it are nonexistent, thus the great importance of papers like Venkatesh et al. that addresses guidelines for mixed-methods research.

(4) Similar to what happens with interdisciplinary work, the publication road for integrative intradisciplinary work can be hard, as often reviewers struggle to assess what a good mixed approach really is.

I also would like to point out that the valiant efforts to characterize and promote multimethods or mixed-methods so far in the IS literature have been primarily undertaken within the behavioral and organizational research streams. They have focused on how to combine qualitative and quantitative methods. I propose that in addition to combining methods, we should think about a broader integration at the higher level of research streams and general methodologies.

Finding Commonalities in Specific Methods

My first point in proposing more integration of research paradigms is about reinforcing the notion that in our mission to advance science and knowledge, our different efforts already share common principles at different levels. Let me start with highlighting commonalities that I find exist in the methodologies that are used by different camps. Here are some thoughts about common concepts that run across different methods and approaches.

New Theory Development

New theory development through a practical method of observation and interpretation has been identified as the primary purpose of the grounded theory research paradigm (Glaser and Strauss 1980). Historically, the methodology was developed as a reaction to the positivism that had permeated most social research. Grounded theory focuses on the interpretive process by analyzing the "actual production of meanings and concepts used by social actors in real settings" (Gephart 2004, p. 457). It is a pragmatic approach to social science research where empirical reality is seen as the ongoing interpretation of meaning produced by individuals engaged in a common project of observation (Suddaby 2006). New theory development can be achieved by combining the two key concepts of *constant comparison*, in which data are collected and analyzed simultaneously, and *theoretical sampling*, in which decisions about which data should be collected next are determined by the theory that is being constructed (Glaser and Strauss 1980).

When I first was exposed to the concept of grounded theory, I couldn't help drawing a parallel (at least in the objectives) with efforts with theory building in research that utilizes data mining and prediction models in the environments of large Internet data sets. In these environments, researchers employ computer algorithms to evaluate and uncover patterns out of detailed data without following a prescribed theory. The outcome relates to the "empirical reality" resulting from the pragmatic approach of observation of the social actors of grounded theory. With the supervision of the researcher, machine learning algorithms can be "trained" to perform steps similar to both constant comparison and theoretical sampling. Actually, this parallel between theory building efforts in the two paradigms was also identified in Shmueli and Koppius (2011) who published an interesting, thought-provoking research essay in *MISQ*. Here is an excerpt from page 557:

> The new types of data sets available today are rich in detail; they include and combine information of multiple types (e.g., temporal, cross-sectional, geographical, and textual), on a large number of observations, and with

> high level of granularity. Such data often contains complex relationships and patterns that are hard to hypothesize, especially given theories that exclude many newly measurable concepts. Predictive analytics, which are designed to operate in such environments, can detect new patterns and behaviors and help uncover potential new causal mechanisms, in turn leading to the development of new theoretical models.

Some examples of the success of the approach of utilizing data mining methods for theory development in rich, detailed data sets come from the online auctions environment, where new theoretical insights about bidder behavior were uncovered, for which traditional economic theory offered no explanation (Bajari and Hortacsu 2004; Bapna et al. 2004). I would also refer to the rich and growing area of personalization and online recommendation systems, where predictive models are used to find uncovered co-occurrence of patterns and associations that lead to new theoretical developments about online consumer behavior (for example, Saar-Tsechansky and Provost 2007; Tuzhilin 2009).

My point in establishing the connection between theory building through machine learning models and the grounded theory approach ties back to the point made by Glaser and Strauss: "quantitative data are often used not for rigorous demonstration theory but as another way to discover more theory" (p. 235).

Latent Variables

Let us go one level lower and look at the methodology layer of two different streams: (1) economics of IS and (2) positivist, explanatory behavioral research. Both approaches rely heavily on statistical methods: multivariate models and econometrics. Very often in IS research, the latent or unobservable variables are what we are interested in: attitude, motivation, propensity, etc. Not surprisingly, latent methods have become increasingly popular in both econometrics and survey-based research. In IS econometrics research, hidden Markov models, as recently utilized in Sahoo et al. (2012), have gained in importance, as have latent methods in clustering (Bapna et al. 2011) and structural econometrics models. In quantitative behavioral IS research, SEM (structured equation modeling) also focuses on relating latent variables to observable measures. Statistics provides the common ground of dealing with latent variables in both research paradigms. It shouldn't be that hard for researchers from one side to understand the methods of the other side.

One shouldn't be surprised with these commonalities because, after all, we are talking about statistical estimation methods in both cases. The point here again is to bring to attention that there is common ground across the statistical techniques that are employed by different IS research streams. I have run into behavioral researchers who claim they don't understand econometrics and also economics of IS researchers who know nothing about SEM and the associated statistics techniques. Essentially the concepts behind these techniques and their estimation are very similar.

Weights Estimation

Going yet one level deeper in the application of the methods, let's look at estimation approaches. To solve SEMs, PLS (partial least squares) and associated techniques have become one of the methods of choice in behavioral and organizational quantitative research. Isn't it fascinating that the algorithm for computing and updating the matrix estimates for the underlying regressions follows the same mechanics as the one used to estimate the weights of the nodes and links of the machine learning technique neural networks? There are input nodes, hidden (latent) nodes, paths, and weights to be estimated. The estimation follows an iterative algorithm and there are rules for convergence. Again, the similarities shouldn't be surprising as both methods rely on linear relationships and latent variables; in the neural networks case, they are called hidden layers and carry no meaning. Nevertheless, the underlying algorithmic structure is the same in a behavioral confirmatory tool and a machine learning predictive modeling analytics tool.

Mixed-Method Integration

Venkatesh et al. do a very good job characterizing how qualitative and quantitative approaches have been integrated in IS research. They identify seven different, high-level purposes of mixed methods research and illustrate how each purpose has emerged in IS research. I reproduce here the first two columns of their Table 1.

Table 1. Purposes of Mixed-Method IS Research	
Purposes	**Description**
Complementarity	Mixed methods are used in order to gain complementary views about the same phenomena or relationships.
Completeness	Mixed methods designs are used to make sure a complete picture of a phenomenon is obtained.
Developmental	Questions from one strand emerge from the inferences of a previous one (sequential mixed methods), or one strand provides hypotheses to be tested in the next one.
Expansion	Mixed methods are used in order to explain or expand upon the understanding obtained in a previous strand of a study.
Corroboration/Confirmation	Mixed methods are used in order to assess the credibility of inferences obtained from one approach (strand).
Compensation	Mixed methods enable compensation for the weaknesses of one approach by using the other.
Diversity	Mixed methods are used with the hope of obtaining divergent views of the same phenomenon.

At the current juncture of the information revolution, when IT-related innovations keep adding new products, services, changing relationships between individuals and between individuals and organizations, shaping new societal environments, the emerging phenomena of interest do require integration of research approaches at the research stream level. I believe that the classification of purposes above can be easily extended and adapted beyond the combination of qualitative and quantitative methods to the combination of streams and sub-streams of IS research.

Design Science Research

A particular set of research phenomena in the IT innovation era, which require integration at the stream level, relates to design science. These are great opportunity times for design science research: conceptualizing, creating, testing innovative IT artifacts, and evaluating their impact. Advancing design science absolutely requires an intradisciplinary research approach with purposes similar to the ones in Table 1: complementarity, completeness, developmental, expansion, corroboration, compensation and diversity.

Design science, economics of IS, and behavioral IS go hand in hand in developing, testing, and validating the desirable proof-of-concept, and the higher levels of proof-of-value and proof-of-use (Nunamaker and Briggs 2011). As technology enables more sophisticated and complex applications that include economic transactions and interactions, economic principles and behavioral principles should be used together in the assessment of value creation of design science artifacts.

An example of successfully combining economic, design science, and behavioral approaches is the intradisciplinary research out of Minnesota related to combinatorial auctions. Based on the necessity demanded by the new information-rich, customer-centric online environment, Adomavicius and Gupta (2005) first proposed an IT artifact, a new method of bidding in online combinatorial auctions, guided by a real-time feedback mechanism. The artifact itself and its proof-of-concept had an impact in advancing the economic theory of online combinatorial auctions. However, the real and broader impact of the research had to do with the subsequent efforts of proof-of-use and proof-of-value, for which the authors incorporated economic and behavioral research streams and their methods (Adomavicius et al. 2012, 2013; Adomavicius, Gupta and Sanyal 2012).

Other successful examples of the deployment of intradisciplinary IS research in the context of design science is currently taking place at the University of Arizona. Several intradisciplinary efforts are under way to tackle the broader topic of "trust and deception detection" with the use of advanced physiological and cognitive sensors, well-designed lab experiments with real subjects, and massive data analytics, surrounding questions around several IT artifacts. Proofs of concept, use, and value are being sought in a multimethods environment. This research relates to border security and is being funded by the Department of Homeland Security (http://www.borders.arizona.edu/cms/).

Behavioral Economics as a Platform for Intradisciplinary IS Research

The second part of the 20th century saw great advances in the integration of psychology research and economics. Built on the seminal work of Herbert Simon (bounded rationality), Amos Tversky and Daniel Kahneman (prospect theory), Gary Becker, and many others, the field of behavioral economics emerged showing that psychology and economics are faces of the same coin, when it comes to explaining human behavior.

I believe there are great opportunities for IS research to use behavioral economics as a reference discipline to intradisciplinary work. I anticipate a rich environment for combining the various methods, qualitative and quantitative, experimental approaches, empirical models, and big data analytics to study our emerging phenomena in test beds that require a combination of multiple approaches that can involve lab experiments and analytical and empirical modeling. With the increased availability of observational data of human behavior (big data from social media, sensors, web sites, etc.), the different research subareas can gain and learn from each other. The key again is to rigorously understand the fundamental methodologies to build a solid platform for intradisciplinary IS.

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