Causality: The elephant in the room in information systems epistemology

Gregor, Shirley; Hovorka, Dirk S.

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CAUSALITY: THE ELEPHANT IN THE ROOM IN INFORMATION SYSTEMS EPISTEMOLOGY

Shirley Gregor, The Australian National University, Canberra, ACT 0200, Australia, Shirley.Gregor@anu.edu.au

Dirk S. Hovorka, Bond University, Gold Coast, QLD 4229, Australia, Dirk_Hovorka@bond.edu.au

Abstract

Causal reasoning is central to scientific practice and to everyday life, yet has received scant attention in Information Systems epistemology. This essay identifies six types of causal analysis that can be used in IS research: regularity, counterfactual, probabilistic, manipulation, substantival (mental), and enabling condition analysis. A framework is developed for application of the different types of analysis in terms of two dimensions; planned versus emergent systems and prescriptive versus descriptive modes of research. It is shown how the different types of analysis can be used in each cell of the framework. The identification of the substantival and enabling condition types of analysis for Information Systems research is novel. Further work is indicated, particularly with respect to probabilistically necessary and sufficient conditions, qualitative evaluation of causal chains, and the plausibility of claims for causality with some statistical methods in common use.

Keywords: Causal analysis, causal conditions, information systems, epistemology

1 Introduction

Reasoning about causality and the identification of relationships between causes and effects is central to scientific thought and to everyday human choice and action (Pearl, 2000; Shadish, Cook and Campbell, 2002). Causal analysis has significance in the "sciences of the artificial", those branches of science that concern artificial objects and phenomena that are created by human activity, rather than natural processes (Simon, 1969). Simon included computing, economics, engineering, operations research, management science, medicine and social planning amongst the sciences of the artificial. In these sciences, the objects, processes and knowledge that are produced are utilized by human actors in ways that can have far-reaching consequence: for example, in the administration of drugs in a health program. Medical science provides a good example of the recognition of the need for rigorous analysis of causal relationships in complex socio-technical environments.

Information systems (IS) concerns human-made technology-based systems, social systems, and the phenomena that arise when the two interact (Lee, 2001). Causal reasoning about the relationships among the design features of information technology (IT) related artifacts[1], human capabilities and behavior, and outcomes should be central to research practice. A lack of sound causal reasoning about IT related artifacts can have serious consequences: for example, lack of knowledge about the causal link between poor IT governance and system failure can have disastrous outcomes for an organization (Avison, Gregor and Wilson, 2006).

Despite the need for causal reasoning in IS/IT epistemology, there is surprisingly little attention paid to the topic. The concept of causality is difficult in itself and drawing valid inferences about causal relationships can be extremely complicated in complex environments. In quantitative IS research, the prevalence of modern multivariate statistical methods has privileged a focus on correlations rather than causality (Pearl, 2000). Qualitative IS research is challenged by complex contexts in which determining direct effects on outcomes is difficult. Although Shadish et al. (2002) discuss causal inference in social sciences research in general, there is little to inform IS research epistemology in particular, where we will argue that the inclusion of designed artifacts intended to bring about desired outcomes as the focus of research means that we need to include specific forms of causal analysis.

Few research studies explicitly reflect on whether and how causal reasoning has occurred. With some approaches researchers do not conform to recommended practice for inferring causality for their chosen methods. Examples are cases where a study with a cross-sectional survey and structural equation modelling includes claims for support for causal statements, whereas authorities on structural equation modelling say that results should not generally be interpreted in this way. That is, the "the interpretation that direct effects in a path model correspond to causal relations in the real world is typically unwarranted" (Kline, 2005 p 118). The extant literature on causality in IS epistemology remains sparse, apart from limited coverage in Gregor (2006), Hirschheim (1985), Markus and Robey (1988), and Mithas and Krishnan (2009). Thus, causality has become something of "an elephant in the room": it is of vital importance yet it is receiving little attention.

Our aim in this essay is to argue for a greater focus on causal reasoning in IS epistemology and to provide an initial framework for causal analysis. The essay identifies six types of causal analysis and shows causal reasoning applied in two modes of research in IS: the interior prescriptive mode (the construction of artifacts) and the exterior descriptive mode (the study of artifacts in use).

[1] The term "IT related artifacts" covers a broad range of the subject matter of IS research, from more technical artifacts (e.g., decision support systems, ERP, mobile devices, electronic auctions) to more socio-technical artifacts (e.g., IT project management methods, IT change management models, social networks).

2 History of causal theory in brief

The enormous depth and breadth of the literature on causal theory limits our treatment to highlights of a few key developments which serve to frame our usage in this work. The concept of causality can be traced back to Aristotle and the early Greek philosophers, who recognized a fundamental distinction between descriptive knowledge saying *that* something occurred, and explanatory knowledge saying *why* something occurred. Notably, Aristotle's doctrine identified four causes (*aitia*) (Hooker, 1996):

- *Material cause*: “that out of which a thing comes to be, and which persists” (that is, what a thing is made of)
- *Formal cause:* “the statement of essence” (that is, the form and pattern that define something as "this" rather than "that")
- *Efficient cause*: “the primary source of change” (that is, the designer or maker of something.)
- *Final cause:* “the end (*telos*), that for the sake of which a thing is done” (e.g., the need for accounting control causes accounting IS implementation)

Notably, modern science has largely focused on the equivalents of material and efficient causes. But increasing interest in the “science of the artificial” (Gregor, 2009; Lee, 2010; Simon, 1969) has reinvigorated reasoning about final causes for purposefully created artifacts. Practical criteria for determination of causality were presented by J. S. Mill (1882) as: (1) the cause has to precede the effect in time, (2) the cause and effect must be related, and (3) other explanations of the cause-effect relationship have to be eliminated (Shadish et al., 2002). Mill’s criteria are still relevant, but they are overly simplistic when dealing with the construction of IT based artifacts.

Pearl (2000) notes the prediliction to avoid causal reasoning amongst statisticians that followed from Pearson (1911) who proposed discarding cause and effect as a ”fetish” and part of the inscrutable arcuna of modern science” (p. iv), substituting correlation tables in its place. Pearl notes that this tendency has continued onto the present day – no doubt a partial explanation of the ”elephant in the room” phenomena in IS research. Randomized experiments are still the preferred method for testing causal relations in mainstream statistics and science (Pearl, 2000; Shadish et al. 2002).

In this work we do not address the long-standing debate regarding the existence of “real” causes. Rather, as Hume did, we recognize that reasoning about causality is an inescapable and a necessary part of human and scientific life, although the causal inferences cannot be drawn with the force of logical necessity. The coverage of causal analysis that follows recognizes that many different approaches to causal analysis are possible. The approach that is taken rests on the adoption of some form of realist ontology, although not necessarily naïve realism. Further, our arguments are based on a position that rejects extreme relativism. We believe that some analysis and arguments are to be preferred to others because they can be better justified by reference to supporting evidence and relevant existing knowledge (Toulmin, 1958).

As the topic of causal analysis is so complex, we will begin with an example of causal reasoning in science to introduce the problem area (Exhibit 1). Hempel (1966) provided this example to show important aspects of scientific enquiry in a monograph on the philosophy of the natural sciences. What is important for our argument is that the context has commonalities with IS. There is a rich and complex socio-technical situation (a hospital) where a lack of knowledge is having serious practical consequences (women are dying) and central to the scientific enquiry is an intervention/artifact (effective hand-washing routine) designed to alleviate a practical problem.

This example shows several types of causal inference. There is *counterfactual analysis* in the comparison of situations where mortality rates are higher and lower in field experiments. There is *manipulation analysis* where Semelweis saw a direct causal link between an action (a scalpel cut) and the development of a fever similar to childbed fever. We can also distinguish a case of *mental* or *substantival* causality. The decision to try hand-washing as a preventative method appeared to come from Semmelwais' mental efforts: it was an act of creativity with no evident preceding external cause (nothing compelled him to think of this solution and there was no existing scientific theory to suggest it).

Exhibit 1 Semelweis' work on childbed fever in the 19th century (Hempel, 1966)

Semelweis, a physician in a Vienna hospital, was confronted by a distressing rate of mortality for women delivering babies in the First Division ward in the years 1844 to 1848. The rate was much higher than in the Second Division. Explanations for the difference included: "atmospheric-cosmic-telluric changes", overcrowding, and rough examination by medical students. Semelweis was able to rule out these explanations by showing that there was no substantial difference in these supposed causal factors between the First Division and the Second Division. Another explanation was that a priest making ceremonial visits to the First Division terrified the patients, but he was not visiting the Second Division. A further cause postulated was that women in the First Division were lying on their backs during delivery, but on their sides in the Second Division. Semelweis was able to rule out both these putative causal explanations by conducting experiments: having the priest visit the Second Division and making the women in the Second Division alter their position and observing that neither change altered the differential rates of fever.

Serendipity provided Semelweis a clue. A colleague received a cut from a scalpel that had been used in an autopsy and developed a fatal fever similar to childbed fever. Semelweis hypothesised that some cadaveric matter contaminated the victim and caused his death. The situation could be the same as with the First Division, as physicians were coming straight from performing autopsies to delivering babies. Semelweis created an intervention requiring all medical staff were to wash their hands in a solution of chlorinated lime before beginning examinations. The mortality rates in the First Division then dropped to being on a par with the Second Division.

This example provides a concrete example of how different types of causal reasoning can be employed with direct practical effect. It is given here as an orientation towards the remainder of the essay, where the terms used are explained in more detail. We will now develop an account of how a number of different types of causal analysis can be systematically employed in IS research.

3 Types of causal analysis

A cause is seen as an event or action which results in a change of some kind. If there is no change of state then there is no cause and no consequent effect (Schopenhauer, 1974). Two main classes of causation can be distinguished: *event causation* and *agent causation* (Kim, 2011). Event causation is the bringing into being of an event by some other event or events. Agent causation further distinguishes the act of an agent bringing about change.

The following discussion identifies six types of causal analysis, some of which can be inter-related.

First, four prominent approaches to analyzing causality are identified, following (Kim, 2011):

1. *Regularity analysis* (constant conjunction or nomological analysis): This type of causality is common in the natural sciences and is based on uniform and constant covering laws. "There are some causes, which are entirely uniform and constant in producing a particular effect; and no instance has ever been found of any failure or irregularity in their operation" (Hume, 1748 p 206). Due to the complexity and variability of human behavior, this type of regularity should not be expected or sought in the social sciences (Fay, 1996; Little, 1999).
2. *Counterfactual analysis:* This means of analysis posits that what qualifies an intervening event or agent as a cause, is the fact that if the intervention had not occurred, the outcome would not have occured (Collins, Hall and Paul, 2004). For example, if one group in a randomized experimental trial has a treatment while a control group does not, and the treatment group exhibits higher performance, then we can claim that the treatment led to the improved performance, because there are no other differences between the group.

3. *Probabilistic analysis:* In contrast to covering laws Hume (1748, p 206) recognised that "there are other causes, which have been found more irregular and uncertain; nor has rhubarb always proved a purge, or opium a soporific to everyone...". The lack of a closed system and the variable effects of extraneous influences makes probabilistic analysis suited for the social sciences and the sciences of the artificial. Causal statements take the form, "to say that C is the cause of E is to assert that the occurrence of C, in the context of social processes and mechanisms F, brought about E, or increased the likelihood of E" (Little, 1999 p 705).
4. *Manipulation analysis:* This analysis entails a conception of causation in which an intentional intervention in a system will influence the outcome. That is, the cause is an event (an act) that we can manipulate to bring about an effect: for example, pressing a switch turns a light off. This practically oriented conception can identify knowledge useful for specific kinds of prediction problems. It contains elements of variance such that probabilistic effects can be accounted for. More importantly, it provides a separate inferential step which allows us to differentiate the case where two variables are correlated, from the case where it is claimed that one variable will respond when under manipulation by the other (Woodward, 2003).

Agent causation analysis in general could be seen as reducible to manipulation event analysis. That is, the movement of one's hand (an event) caused the light to come on (another event) and both these events were preceded by other events in a chain (walking through the door, perceiving that the room was dark), that is, it is a consequence of the agent's beliefs, attitudes and environmental inputs (Pearl, 2000). But reduction to physical events fails to account for the intention of the actor where mental effort has causal agency in the performance of a physical event.

The latter form of agent causation is not easily reducible to event analysis, and is referred to as *mental* or *substantival causation* (Kim, 2011). This form of causation is particularly relevant in design disciplines and we will distinguish it as a fifth form of causal analysis in our framework:

5. *Mental (substantival) causation analysis*. This form of analysis recognizes the creation of a novel artifact. Examples include inventions such as the first telescope, the first bicycle, and the first decision support system. Recognizing this type of causality requires recognition that humans have intention and can choose to do or create things that did not exist before. This conception of causation recognizes the deliberative behavior of humans in action (Pearl, 2000)[2] and overcomes the criticism that causal reasoning must exclude the creation of novelty (Bunge, 2008). In IS, Goldkuhl (2004 p 68) uses the terms "inside development" and "idea based design" to refer to similar concepts. We will distinguish this type of causation separately, because of its implications for design work.

At this point, it is necessary to discuss the concepts of necessary and sufficient conditions, probabilistic analysis, and the distinction between active causes and static contextual causal conditions. The issue of necessary and sufficient conditions, are central to many arguments for causality. For example, a counterfactual argument rests on the claim that effect *E* would not have occurred if cause *C* had not occurred; in this case *C* is a *necessary cause* for *E*. To use a highly simplified example, the application of a burning match to a material could be seen as a necessary cause for a fire to light. However, there are other *contextual* conditions that are also needed for a material to ignite: for example, there must be enough oxygen present. Thus, though the match is necessary, it is not sufficient to cause a fire in the absence of other contributing contextual factors. But, taken together, the active cause and the causal condition (striking match plus oxygen) could be considered necessary and sufficient conditions for the fire to light. But even in simple cases, there are problems in specifying all of the contextual conditions that are needed for both necessity and sufficiency. The active causal intervention of the burning match might not be necessary, because another active event could cause the fire to light (e.g. lightning, an electrical wiring fault). Further, it is difficult to specify all the contextual conditions that are necessary - such as specification that the

[2] The issue of the connection between the mental deliberations of humans and their consequent observable actions is part of a larger mind-body problem (see Kim 2011), which is beyond the scope of this essay.

material must be flammable and dry. This suggests that causal analyses seeks to identify *constellations of causes* that collectively influence the effect. In addition there are *chains of causality* from events or agents proximate to the phenomenon to those more spatially or temporally distal to the phenomenon, such that manipulation of many parts of the chain will alter the effect. The problem of complete determination of necessary and sufficient conditions verges on the impossible outside very simple, well-defined, and closed systems.

In socio-technical systems we have to deal with situations where the number of potential causal conditions is large and there can be considerable uncertainty about the nature of linkages between cause and effect (Fay and Moon, 1996). Problem spaces in which artifacts will be implemented only rarely (if ever) fit *ceteris paribus* (all else being equal) conditions. In such situations it is useful to consider probabilistic reasoning about necessary and sufficient conditions. Pearl (2000 p 284) shows how the *probability of necessity* can be thought of in terms such as "the probability that disease would not have occurred in the absence of exposure [to an insect bite]". The disease might occur in only 1% of cases without exposure. If you are not exposed you have a 99% chance of not getting the disease - exposure is "almost" a necessary condition. In IS for example, the probability of necessity for module testing to ensure all errors are detected is 99% (1% of cases would be error-free if no module test occurs). The probability of necessity emphasizes the absence of alternative causes that are capable of explaining the effect.

Similarly, the *probability of sufficiency* can be expressed in terms such as the probability that a healthy unexposed individual would have contracted the disease had he or she been exposed. The disease might follow exposure in 70% of cases. Similar reasoning is needed in IS. The probability of sufficiency of a committed project champion is 80% (80% of cases with a committed project champion will be successful). The probability of sufficiency emphasizes the presence of active causal processes that can produce the effect. The intricacies of determining necessary and sufficient conditions is detailed here because it is a common form of analysis even if not recognized explicitly. Examples are analyses where an attempt is made to identify "key" factors that are either necessary or sufficient, or both, for some outcome to occur, as in key factors for project success or for useability.

Finally in human-computer interactions, enabling causal conditions are captured by the idea of "affordance". For Norman (1988), the affordances of an object are the action possibilities that are perceivable by an actor because of the object's design characteristics (e.g. a door that has no handle is to be pushed rather than pulled.) Although these effects cannot be controlled or predicted, conditions which enable emergent behaviors and outcomes to arise from the lack of tightly coupled integration of components can be *designed for* in the secondary design of information systems (Germonprez, Hovorka and Callopy, 2007). Systems in use consistently show unexpected consequences (Dourish, 2006; Winograd and Flores, 1986). Ciborra (2002 p 44) notes that new systems of value emerge when users are "able to recognize, in use, some idiosyncratic features that were ignored, devalued or simply unplanned."

Both the concepts of affordance and secondary design are important because they enable or constrain actions with an artifact that cannot be foreseen at the time of the design. Conditions support both event and agents as causes in an indeterminate chain of causes and effects. We will recognize the importance of this type of causality by distinguishing it as a sixth type of causal reasoning in IS:

6. *Enabling causal condition* analysis involves consideration of how artifact characteristics and contextual conditions affect outcomes. The important characteristic is that the inclusion or exclusion of particular design affordances (Gibson, 1977) or contexts will change the probability of the desired outcomes. For example the scroll wheel on a computer mouse, and roll-over text which informs users what will happen if they select a specific hyperlink encourages specific actions. Another causal condition is the use of component architectures and recognizable conventions (Germonprez et al., 2007) which enable users to recognize conventional functions of component parts which can be reassembled into new patterns or adapted to new task functions.

4 A Framework for Causal Analysis in the Sciences of the Artificial

The analysis of causal mechanisms above has pointed to six types of causality that can potentially be distinguished by researchers in IS. Each of the types of causal analysis can provide insights in IS research, although the socio-technical complexity of designed and implemented information systems renders the logic of uniform and constant covering laws as rare (Fay, 1996; Hovorka, Germonprez and Larsen, 2008).[3]

The framework has two dimensions reflecting the nature of the IS/IT artifact studied and the nature of the research activity. The first dimension recognizes a functional typology of IS such as that proposed by Iivari (2007) (Figure 1).

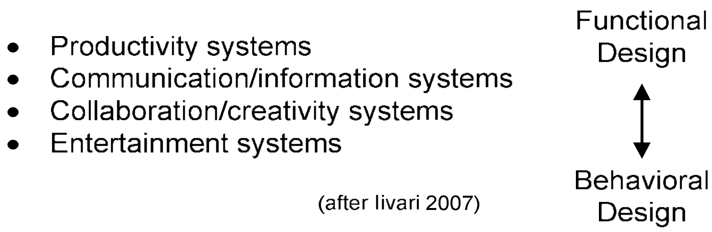

Figure 1. Teleological abstraction of information system typology

This highly abstracted typology identifies a dimension along which most information systems fall. At one end are highly functionalist systems (Hirschheim and Klein, 1989) designed predominantly as productivity systems intended to achieve well defined outputs with maximum efficiency from well understood processes. As the processes, inputs, outputs and interactions are well known and understood, the causal connections and boundaries in the problem space are also well understood, and the outcomes are relatively predictable. Thus specific types of causal reasoning can be applied.

In contrast, behaviorally-oriented design privileges flexibility, creativity, adaptation to new problem domains, and secondary design (Germonprez et al., 2007). This class represents design domains in which the users' behavior and intentions are not only present, but are required by the artifact-in-use. The contexts, tasks, and users are diverse and variable and the systems evolve new patterns of *in situ* use as they are modified. To obtain desired outcomes of system use require types of causal reasoning which are probabilistic and include enabling causal conditions. Examples include design principles for emergent knowledge processes (Markus, Majchrzak and Gasser, 2002) or for tailorable systems (Germonprez et al., 2007). This distinction between teleological goals suggests a dimension of planned-emergent design, which forms one axis of our framework.

The other axis of our framework is formed by a distinction between research that is done in the interior prescriptive mode of design where artifacts are constructed to alleviate problems in the problems space, and the closely linked exterior descriptive mode, composed of the interaction and evaluation of the artifact in its embedded context (Gregor, 2009). The prescriptive mode focuses on how artifacts can be designed and brought into being and creativity can play a part. This mode represents what is commonly understood as the build phase of design science research (Hevner, March, Park et al., 2004), although likely to involve developmental evaluation and observation.

In contrast, the exterior descriptive mode focuses on the artifact-in-use as the artifact is studied as part of a wider system, often by people other than the original designers. The descriptive mode potentially includes all types of investigation, including measures of process output changes, user and management perception studies, outcomes of action-research studies, phenomenological or

[3] That the technical aspects of socio-technical systems are expected to behave in a uniform and predictable manner (e.g. electronic circuitry) leads some researchers to reason in terms of covering laws. This reasoning would occur in some design science work, aspects of software engineering and in computer science.

hermeneutic studies of attached meaning and power structures or resistance. Work in this mode can be advanced to inform future design work in the interior prescriptive mode (see Goldkuhl, 2004; Gregor, 2009; Keuchler and Vaishnavi, 2008). This mode represents what is often termed in IS as behavioral research.

Figure 2 shows the matrix that arises when these two dimensions are considered together, with indicative examples of appropriate causal reasoning given in each cell.

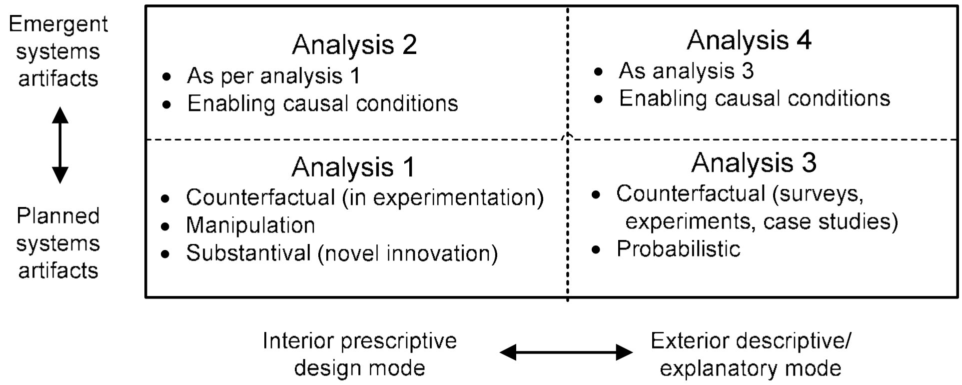

Figure 2. Types of causal analysis for IS research

5.1 Analysis Cell 1:- Prescriptive design of planned systems.

Cells 1 and 2 represent in large part "design science" research activities in IS. Multiple types of causal analysis can be recognized. Manipulation analysis is often used implicitly: that is, our team built this artifact and put it into use, with the implied prediction and expectation of desired outcomes. Here the analysis may consist simply of identifying what intervention will be created by the artifact and what system or behavioral change is expected as a direct result. This analysis can be based on kernel (justificatory) theory which provides support for the causal linkage between manipulation and effect.

Counterfactual and probabilistic reasoning about causality are also used in iterative design processes. That is, the researcher constructs and tests prototypes and observes what results occur. Iterative prototyping is inherently a process of refinement through identification of probabilistic necessary and sufficient causal conditions. Experimentation is common in this process.

An example is given in Codd's work on the relational database model (Codd, 1970; Codd, 1982). Codd made claims about how fewer mistakes would occur with use of relational databases because users would not have to expend so much effort on dealing with the complexity of repeating groups. This is counterfactual analysis in a thought experiment - the removal of the artifact feature of repeating groups from the human-use process is the cause of fewer errors.

Importantly, the designer's thought processes in conceptualizing a problem space and generating ideas for potential solutions are themselves causal mechanisms. In the design of consequential management theory, Argyris (1996) suggests that the human mind functions as the designing system. This process is what we term *substantival causality* (mental causation). Much design theory building is non-rational, abductive and unstructured. In many cases we cannot say where the idea for the design came from, or why it is as it is, as human creativity and invention have come into play.

5.2 Analysis Cell 2 : Prescriptive design of emergent systems

Although it seems counter-intuitive to conjoin design and emergence, there is a strong impetus to create types of artifacts whose functions, applications, and behaviors are flexible, agile, and emergent. Therefore, analysis of "enabling casual conditions" is warranted. As specific emergent phenomena cannot be predicted, the principles which will improve the likelihood that general desirable characteristics (e.g. flexibility, mutability, ability to be reconfigured) will emerge are selected. These are *conditional causes* where the designer considers enabling (or disabling) environmental conditions which increase the probability of an outcome (Sloman, 2005). Examples include identification of causes which are likely to create perceived affordances or secondary design functions or content. Principles such as component architectures, recognizable conventions, and metaphors (Germonprez et al., 2007) suggest probabilistically necessary but not sufficient causal conditions for emergent system behavior. Counter-factual analysis can be applied in reverse to identify factors or processes which rigidly couple system components to the world, resulting in rigid, inflexible system use (Winograd et al., 1986).

5.3 Analysis Cell 3: Planned systems in explanatory/descriptive mode

Cells 3 and 4 correspond largely to "behavioral science" research, as commonly understood in IS. Again, many methods for causal analysis can be employed. Counterfactual analysis as advanced by Shadish et al. (2002) for experimental and quasi-experimental work is useful. For example, claims for the advantages of the relational database model in terms of the hypothesised reduction in programmer error and greater ease-of-use could be tested in formal experiments.

Claims for causality can be examined in terms of manipulation analysis when process models are examined. Case studies can also use counterfactual analysis in pattern analysis. Braa et al. (2007) examined cases of health standards development in several countries. Using a form of counterfactual analysis, chains of events (process models) in each case were analysed and contrasted to determine what did and did not occur in each country.

Issues concern the use of statistical methods in survey-type work, when there is no experimental design. In statistics, authorities cast doubt on methods for attributing causality apart from randomized experiments (Pearl, 2000). Shadish et al. (2002) believe that experiments are the best approach for determining causal relationships and non-experimental statistical methods in common use are not regarded as valid for causal analysis. The underlying problem is that correlations indicating relationships between constructs can be a result of some other unknown factor (the "true" cause) and the absence of any observable relationship can result from an endogenous moderating factor that has not been recognized. In cross-sectional surveys evidence for the time order of the occurrence of variables can be lacking thus diminishing the temporal ordering necessary for causal claims. Claims for support for causal relationships should be made very carefully.

5.4 Cell 4: Emergent systems in explanatory/descriptive mode.

Attribution of causality in this situation is difficult precisely because the outcomes emerged from the *in situ* use of the artifact. Yet as Gregor and Jones (2007) note, "the ways in which [artifacts] emerge and evolve over time and how they become interdependent with socio-economic contexts and practices" (p 326) is a key unresolved issue for design. Numerous researchers have noted that artifacts are often used in ways they were not intended due to tinkering or secondary design of the system (Ciborra, 2002; Hovorka and Germonprez, 2010) and the inability of designers to share the same model of the design space as held by the users (Dourish, 2001). As noted in Cell 2, design principles to enable or constrain emergent system behaviors can be designed into the artifact, but particular emergent characteristics cannot be predicted. In the evaluation of emergent system behaviors, probabilistic counterfactual analysis may be possible and even desirable. Determination of what causal mechanism was present that enabled emergent behaviors broadens the scope and fruitfulness of theory that informs subsequent design.

6 Application of the Framework

Space precludes a full analysis of causal reasoning in practice in IS research against the framework. However, Exhibit 2 shows a design science case concerned with the design of a system to assist in business process design. The design aspect of this research concerns mainly Cell 1. Cell 3 is involved to some extent for the final tests – where they had moved to analysis of the design in use in a "naturalistic" way. We have chosen this example as the authors give a detailed account of the stages of their research activity.

Exhibit 2 Business Process Modelling Problem (from Kuechler and Vaishnavi, 2008)).

> The problem addressed was the suboptimal design of business process due to ineffective incorporation of "soft context information" in business process modelling. Five steps are depicted in the design science research process: (i) awareness of problem; (ii) suggestion; (iii) development; (iv) evaluation; and (v) conclusion. The authors began by reviewing prior approaches to the problem and then had an "intuition" that the problem resulted from graphical modelling approaches, whereas the researchers' industry development experience made them "wonder" if textual narrative could be a better approach. They identified kernel theories from cognitive science, education, and psychology that provided causal ideas on how "narrative thinking" could be encouraged. A process of construction and iterative refinement of a narrative-based modelling approach led to positive outcomes in pilot testing

In this example the authors identified an "intuition" as leading to their initial primary and novel design idea (substantival causal analyis). There is counterfactual analysis in the use of experiments to test versions of the modelling approach. The causal reasoning is inherently probabilistic - the authors note that they do not have the certainty of natural science theory. Manipulation of soft context information was performed through an iterative design process leading to experimental testing.

The framework may also be applied to sharpen causal reasoning in the exterior mode of research. In Exhibit 3 we provide one example of a common practice in which causal claims are not substantiated by the data[4].

Exhibit 3 Analysing information technology habits (from Lankton, Wilson and Mao, 2010)

> This study examined influences on continued IT usage. The authors concluded that "prior IT use, satisfaction and importance significantly **influence** IT habits (p 300, emphasis added). The study involved a cross-sectional survey of attitudes and usage at one point in time with self-reported measures and analysis with structural equation modelling.

Causal analysis suggests that it is not possible in this situation to tell which events or states came first in time or whether alternative explanations exists. The paper argues that satisfaction influences habit, but an argument could also be made for causality in the opposite direction - high levels of habit lead to respondents saying that their satisfaction is high. The most that should be inferred from the results is that there is association between variables. The results do not provide support for causal hypotheses.

7 Discussion and Conclusions

This essay began with the argument that there is a need for greater attention to causal analysis in IS epistemology - 'the elephant in the room' in IS research. Causal reasoning has been shown to be an essential part of theory construction (Gregor, 2006; Nagel, 1961) and of design, yet it has received limited attention in our literature. The essay provides a starting point for further discussion on the difficult problem of casual reasoning, yet also offers researchers some directions for the types of analysis that can fruitfully be used in different modes of enquiry and with different objects of study.

The essay shows how causal reasoning can be employed in IS research by first identifying six types of causal analysis. The first four types are regularity analysis, counterfactual analysis, probabilistic analysis and manipulation analysis. A further two types are substantival causation and enabling causal condition analysis. A framework illustrating the use of these methods has two different dimensions: (i) a planned versus emergent type of designed system; and (ii) whether the work is in the interior prescriptive mode or the exterior descriptive mode of research. This framework shows that it is possible to distinguish among different types of causal reasoning that can be used in different circumstances in IS research and sometimes in combination.

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[4] It is not our purpose to single out one study for criticism but instead to illustrate how causal reasoning can be used to sharpen knowledge claims from research

A contribution of the paper is that some aspects of causal reasoning are brought to attention that have been little recognized, yet are particularly important for IS. First, we have identified *substantival causation* as a relevant type of causality in the instance of new artifacts or new theory which result from mental activity and are not directly dependent on any event or external agent. In fact, in design work the novelty of the work is an important claim in making a contribution – something rewarded in patents for some types of artifacts. Second, we have discussed the idea of *enabling causal conditions*, which are aspects of a designed artifact that encourage (or discourage) specific outcomes.

There are implications of our discussion that could profitably be explored further. We have discussed the ideas of probabilistic causal necessity and sufficiency (Pearl 2000), which have received little attention in our literature. We cannot expect the certainty of law-like statements in IS: we would do well to investigate in more detail methods for designing and evaluating phenomena governed by probabilistic causal relationships. Further work is required to develop specific research methods for identifying causal relationships such as the "hierarchy of evidence" approach established in evidence-based medical practice (Concato, Shah and Horwitz, 2000).

In addition, evaluation of artifacts is often a binary succeed/fail determination. For example, in a review of 100 evaluations of medical computerized decision support systems Garg et al. (2005) reports that the majority of studies evaluate simple positive/negative outcomes for the dependant variable. But a causal analysis in the evaluation might reveal where in the *chain of causal events or agents* the system failed, thus allowing an incremental design change. This alteration in evaluative reasoning signifies a fundamental shift from design theory falsification to identification of the ancillary assumptions surrounding a potentially robust theoretical core.

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