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The significant others of subjective norm - A scientometric study of subjective norm in IS top-journals over two decades

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USING INTERPRETIVE STRUCTURAL MODELING TO UNCOVER SHARED MENTAL MODELS IN IS RESEARCH

Abstract

The role of grounded approaches has been advocated for long in IS research. However, the inherent subjectivity of such approaches and the apparent lack of a basis to validate or even replicate such research has often been the subject of debate among IS researchers. As a result, many IS researchers tend to fall back on variance-theoretic approaches to conceptualize, design and operationalize their research. In this paper, we show how a grounded approach, interpretive structural modeling (ISM), can be used to qualitatively elicit individual cognitive structures. Further, we show how it can be applied to derive the shared aspects of such a structure across many individuals. We use the well-known technology acceptance model (TAM) to demonstrate the utility of our approach. We conclude the paper by discussing the strengths and weaknesses of this approach.

Keywords: Interpretive structural modeling, information system, user acceptance, inductive research, research methods

1. INTRODUCTION

ISM is a graph-theoretic method that belongs to the causal mapping family of approaches. It can be used to address problems that are complex and subjective. The ISM approach is useful when a multilevel research design is required where the outcome of the research can not be predicted based on available research (Klein and Kozlowski, 2000) – implying the use of both theory- and data-driven approaches for research.

Our objective in this paper is to demonstrate the effectiveness of interpretive structural modeling (ISM) in carrying out inductive research in information systems (IS). We have focused on inductive research (data-driven) because of the relative paucity of such research in the IS literature. While we believe that inductive approaches have the potential to contribute significantly to both theory and practice, we are also aware that theories that are grounded in data tend to be relatively harder to defend. The essential premise for the use of such approaches by a researcher tends to be that existing theories do not account for the complex phenomena that a researcher faces. It is implicit in inductive approaches that a careful study of the phenomenon will reveal the hidden patterns that a researcher believes exist.

Using the ISM approach, we suggest a way to *efficiently elicit* and *synthesize* user responses with respect to complex phenomena. We demonstrate that ISM can help to operationalize research approaches that can be considered a grounded theory by using graphical techniques to extract underlying structures from data. These structures would form what is often the outcome of grounded theory – revealed thought patterns. We believe that individuals share aspects of cognitive structures that they form about technology and its use. Such shared aspects across individuals can be used to develop theoretical models which can be tested and validated subsequently. We refer to the shared aspects of cognitive structure across individuals as shared mental models in this paper.

We apply non-directed and non-model-driven approach of ISM to *generate* a well-accepted and well-known theoretical model, technology acceptance model (TAM). We would like to clarify that the focus of this paper is not to replicate or revalidate TAM model but to just use it as an example to demonstrate the application of ISM approach to generate theoretical models in IS field. By showing that such theory-generation is possible, we hope to persuade IS researchers to employ this technique appropriately in settings or phenomena for which theories do not yet exist. While other causal mapping techniques have been used in IS research (Nelson et al., 2000; Tan and Hunter, 2002), the ISM approach is different in that it is relatively more efficient (in some cases) and lends itself to being replicated more effectively.

Since we are not sure about the level of familiarity with ISM methodology among IS researchers, we introduce ISM methodology first. We then describe how the characteristics of problems (especially complexity and subjectivity) that IS researchers face make the problems well suited for being scrutinized with ISM. We then take up a well-tested theory in IS research (the technology acceptance model - TAM) and show how ISM can be used effectively to develop a TAM. After analyzing the results, we discuss the implications of ISM for IS research in general and elaborate on its strengths and weaknesses. Finally, we suggest areas of IS research that could benefit from the use of ISM.

The contribution of this paper lies not so much in the novelty of the particular finding – but in the novelty and potential of data collection and analysis and how ISM approach can be used in IS research. Since we were able to recreate the TAM structure, we are encouraged to suggest ISM as a viable research approach for many IS research problems that are inherently inductive and qualitative in nature.

2. EXPLANATORY FRAMEWORKS IN IS RESEARCH

We start with the premise that no IS research is either completely inductive or completely deductive. To that extent, development and/or extension of the theoretical framework is often the precursor to empirical support for that theory. However, a major problem with existing approaches to theory development (and research, in general) in IS is the fragmented adhocracy, a result of the federated research framework at work (Landry and Banville, 1992; Hirschheim et al., 1996). Given the richness of the field and the absence of normative or prescriptive frameworks, researchers and consumers of research (who are primarily other researchers) tend to align themselves with a well-established set of ideas or work on a well-known problem. Researchers usually adopt approaches that tend to reconfirm existing theories in a different context or marginally extend them. In doing so, researchers protect themselves from criticisms from other groups that do not agree with their assumptions or beliefs. This framework certainly allows for a thousand flowers to bloom – and enriches the IS field. However, in being overly theory driven, IS researchers may end up playing to the wrong gallery – that of other researchers. However, if IS is an applied discipline, then practitioner-driven research can also be effectively and rigorously incorporated into the IS research process. Stated differently, research that is grounded in data, and which need not be subjected to the researcher's interpretation, can also be useful to investigate multiple phenomena.

The notion of causality in IS research has long been held to the same standards as those of its stronger and better-established disciplines like psychology and economics. The plurality of perspectives in IS research has certainly led to stronger criticism and a shared awareness/need for rigor. This plurality has also resulted in a variety of "explanation types" in IS research. Since the field of IS is built from both natural and artificial scientific disciplines, Hovorka et al. (2003) argue that explanation types depend on the reference disciples through which research phenomena are understood and research agendas are shaped. Hovorka et al. (2003) provide the following types of explanation types: descriptive/structural explanation, covering-law explanation, statistical relevance explanation, pragmatic explanation and functional explanation. While majority of IS research was categorized as statistical relevance (35%), a significant proportion of explanation in IS research was categorized as descriptive/structural explanation (25%) and framework or model-based (23%). The emergence of process-theory (Soh and Markus, 1995; Crowston, 2000; Kanungo, 2003) perspective[1] in IS research points to the need for alternate methodologies to support descriptive/structural explanation option.

Our approach, in this paper, can be considered to belong to the descriptive and pragmatic explanation categories. We take advantage of the fact that human knowledge, "consists of models constructed by human beings" (Warfield, 1998). Our approach focuses on modeling complex entities created by the multiple interactions of components by abstracting from certain details of structure and components, and concentrating on the dynamics (or linkages) that define the behaviors, properties, and relationships that are internal or external to the system.

3. INTERPRETIVE STRUCTURAL MODELING (ISM)

ISM falls into the soft operations research (OR) family of approaches. Soft OR methods can be used to augment traditional quantitative methods, but do not replace traditional tools and techniques (Glasgow, 2000). ISM is a process that helps groups of people in structuring their collective knowledge. The term ISM refers to the systematic application of graph theory in such a way that theoretical, conceptual, and computational leverage is exploited to efficiently construct a directed graph, or network representation, of the complex pattern of a contextual relationship among a set of elements. In other words, it helps to identify structure within a system of related elements. It may represent this information either by a digraph (directed graph) or by a matrix. Interpretive Structural Modeling results in a "directed graphic representation of a particular relationship among all pairs of elements in a set to aid in structuring a complex issue area" (Porter, et al., 1980).

There are three broad steps for developing an interpretive structural model. Step 1: ISM begins with an issue or problem (Hansen et al., 1979). Step 2: The next step is to identify the elements that comprise the issue context are listed. Step 3: In the third step, pairs of elements are compared graphically or in a relation matrix, using a contextual relationship, which is mostly a verb or a verb phrase. Typical generic verbs are "influences" or "causes" and verb phrase are "leads to" "is more important than". Following the selection of the contextual relationship, a graphic representation of the mental model is constructed using the approach described later in the subsequent paragraphs. Mizuno (1988) describes the relationship diagram as a tool that "clarifies intertwined causal relationships in complex problems or situations in order to find appropriate solutions (p. 87)." The relationship diagram, therefore, provides a visual means of mapping out the causal and/or associated relationships in the development of a coherent theory (Anderson et al., 1994). Warfield and Perino (1999) elaborate on the utility of ISM further as the representation of a problematique because it captures the richness and the variety of complex phenomena. A problematique is a graphical portrayal – a structural model – of relationships among members of a set of problems (Warfield and Perino, 1999).

Application of ISM Approach

Having discussed the ISM methodology, we now demonstrate the application of ISM approach to uncover shared mental models. The shared mental model can be treated as a tentative theoretical framework because it captures how respondents commonly understand and explain a phenomenon under consideration[2]. We applied ISM to a well-studied phenomenon in IS – information system use. We took this approach because we wanted to demonstrate the effectiveness of this technique by validating our

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[1] A process framework is denoted by Y = F(C) where Y is the set of outcomes or consequences of a process, C is the set of considerations or elements in the process, and F is the network linking the considerations to each other and to the outcomes. Process models are often considered to be complementary to models that lend themselves to variance-theoretic approaches – in other words statistical models.

[2] This tentative theory can then be subjected to variance theoretic approaches. For instance, a model generated using ISM could be statistically validated (or, for that matter, invalidated).

results with a well-tested theory. We used ISM (Sage, 1977; Warfield, 1973, 1974) to collect, analyze and synthesize the data. Following the three broad steps described above, we first identified the problem at hand. Our problem was to understand IS use behavior at the individual level. The IS usage context that we focused on was spreadsheet usage. We selected spreadsheet usage because it is a well-known and ubiquitously available application and yet there is enough variety in terms of its use and acceptance in different usage contexts.

The next step was to identify and list the elements that are relevant in the problem context. For this we chose to provide the respondents with a superset of elements from Venkatesh et al's (2003) unified technology acceptance model shown in Table 3. The expectation was that not every user will find every element useful or relevant in the context of IS use. We added an additional element, IT-enabled productivity, to the list of elements from Unified Theory of Acceptance and Use of Technology (UTAUT). This theory is an extension of TAM. Users were given the option of providing any other elements that they believed would influence IS use. As stated before, all research can be construed as part inductive and part deductive. For this research, this step was useful to provide an initial list of elements that each individual user considered to be important to the aspect of IS use. In doing so, we were also able to obtain a set of elements that were common to all respondents.

No.	**Element**	**Definition**
1	Performance expectancy (PE)	Performance expectancy is defined as the degree to which an individual believes that using the system will help him or her to attain gains in job performance.
2	Effort expectancy EE)	Effort expectancy is defined as the degree of ease associated with the use of the system.
3	Social influence (SI)	Social influence is defined as the degree to which an individual perceives that important others believe he or she should use the system.
4	Facilitating conditions (FC)	Facilitating conditions are defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system.
5	Behavioral intention (BI)	Intention to use the information system
6	Use behavior (Use)	Actual use (time spent using the information system)
7	Self-efficacy (SE)	Judgment of one's ability to use a technology (e. g., computer) to accomplish a particular job or task.
8	Anxiety (AN)	Evoking anxious or emotional reactions when it comes to performing a behavior (e. g., using an information system).
9	IT-enabled productivity (IP)	Actual improvements or gains in job performance as a result of using the information system

Table 3. Set of Elements Used in the Study

The third step was to compare pairs of elements graphically or in a matrix. The contextual relationship that we used in this study was "influences." This forms the essence of the inductive process – where each user performs pair-wise comparisons among elements of the set of variables and a final structure *emerges.* It is important to reemphasize at this point that although we limited ourselves to the nine elements of UTAUT, we did not specify a research model nor did we specify any variables to be dependent or independent. This is what makes this approach inductive and the theory emergent.

The data elicitation protocol was based on a structured interview. Every respondent was provided with a 9×9 matrix shown in Appendix A. The user was instructed that she would have to fill out the upper triangular only. To do that, the user would engage in a pair-wise comparison of elements. For instance, to compare the PE and EE pair the user would answer "yes" to only one of the following three questions: Does PE *influence* EE? Does EE *influence* PE? Are EE and PE unrelated? If the element in the row *led to* the column element, it was coded as ⇨. If the element in the column *led to* the row element, it was coded as ⇩. Lack of a relationship was coded as O. While filling out this the researcher (or the research assistant) would also document the reason(s) for why the respondent chose a particular relationship between two elements. These would typically be direct quotes from the respondent explaining her response. As shown in Appendix B, every respondent was requested to make 36 pair-wise comparisons.

We collected pair-wise comparison data from 88 individuals. These individuals were selected randomly from four organizations to which graduate research assistants were provided access. The average time for an interview was one and a half hours. The interviews typically started with the researcher explaining to the respondent the study protocol. Most of the time was used up by the pair-wise comparisons and an explanation of the constructs along the way. The interview typically ended with the interviewer collecting data on the respondent's gender, age (age range), experience with computer use (in years) and voluntariness of use of spreadsheets (descriptive). These data items have not been used in this research paper. The interviewer also collected respondents' justification for their inputs to pair-wise comparisons. This was, typically, a single sentence and, sometimes, a small paragraph.

4. ANALYSIS AND RESULTS

While we collected data based on all the elements shown in Table 3, in this paper we report on a subset of the data – one that pertains to TAM. Table 4 shows how responses were distributed. For instance, we can see that 33 out of 88 respondents believed that *effort expectancy* *<u>influences</u>* *performance expectancy*. In the same cell, 29 out of 88 respondents believed that *performance expectancy* *<u>influences</u>* *effort expectancy* and 26 out of 88 respondents believed that there is no relationship between *performance expectancy* *<u>influences</u>* *effort expectancy*.

	PE	EE	BI	Use
PE		⇩ = 33 O = 26 ⇨ = 29	⇩ = 26 O = 13 ⇨ = 47	⇩ = 31 O = 13 ⇨ = 37
EE			⇩ = 15 O = 7 ⇨ = 65	⇩ = 27 O = 9 ⇨ = 45
BI				⇩ = 13 O = 14 ⇨ = 50
Use				

Table 4. Frequency of Responses (numbers show the frequency distribution of responses)

Each individual's response results in a directed graph. That graph captures how an individual understands the linkages between the elements and can be considered to be the individual's mental model. The shared mental model across individuals is captured by the degree of overlap across all the individual directed graphs. In order to seek out those common patterns from these data, we employed the straightforward counting technique for aggregating data across individuals based on Kanungo et al., (1999). In order to retain the "shared" component of the mental models we had to define a minimal level of sharing. This minimal level was 50%. This means that for a meaningful shared view (or a pattern) of how individuals believed the elements were linked, we opted for a simple majority. While this can be understood to capture the shared variation (to use a variance theoretic term), we also have the option of analyzing and understanding the inputs of those individuals who did not “fit” into the majority view. This will be taken up in the discussion section.

Based on the 50% cut-off, the following relationships (PE → BI, 54.65%; EE → BI, 74.71%; EE → Use, 55.56%; and BI → Use, 64.93%) emerged as being common across a majority of respondents. For the other relationships, no clear relationship emerged as dominant and hence that lack of clarity was coded as the absence of an agreed upon relationship. The final relationship matrix we obtained is shown in Table 5.

	PE	EE	BI	Use
PE		O	➪	O
EE			➪	➪
BI				➪
Use				

Table 5. Final Relationship Matrix

This translates into the binary relationship matrix shown in Table 6. The elements in the diagonal are 1 because every element (from a reachability[3] standpoint) can “reach” itself. As mentioned before, the “V” coding implies that the row variable *influences* the column variable and not vice versa. So, for instance, in the case of PE and BI, PE *influences* BI. That means that the element in row 1 and column 3 (excluding row and column headings) will be 1, while the element in row 3 and column 1 will be 0. The lack of a well-agreed relationship is coded as zeros.

	PE	EE	BI	Use
PE	1	0	1	0
EE	0	1	1	1
BI	0	0	1	1
Use	0	0	0	1

Table 6. Binary Relationship Matrix (1 implies a relationship exists)

Next, we identified the levels associated with each element by identifying the reachability and antecedent sets. This iterative process is shown in Tables 7 and 8. Essentially, for all the reachability sets that are proper subsets of antecedent sets, we associate the same level and eliminate those variables or elements for the next iteration. We do this till we have no more reachability and antecedent sets to compare.

e_i	R(ti)	A(ti)	R(ti) $\cap$ A(ti)	Level
1 [PE]	1	1, 3	1	1
2 [EE]	2	2, 3, 4	2	1
3 [BI]	1, 2, 3	3, 4	3	
4 [Use]	2, 3, 4	4	4	

Table 7. The Reachability Set and the Antecedent Set

[3] “Reachability”, in this case, has to do with relations between elements. Relations between elements are assumed transitive in ISM. In other words, if A “leads to” B and B “leads to C”, then A “leads to C”. From a causality standpoint, every element if perfectly correlated with itself.

Table 7 shows that PE and BE are at the same "level" (level 1) in the hierarchy of the elements that need to be structured. Table 8 shows that BI is at level 2. This partitioning of elements into levels creates the "structural" model that adds value to the graph by preventing it from being a non-directed graph.

e_i	R(ti)	A(ti)	R(ti) ∩ A(ti)	Level
3 [BI]	3	3, 4	3	2
4 [Use]	3, 4	4	4	

Table 8. The Reachability Set and the Antecedent Set -II

The final levels associated with the elements are shown in Table 9. These levels are used to draw the final graph shown in Figure 3.

Level	Elements
1	PE, EE
2	BI
3	Use

Table 9. Final Levels for Elements

The final structure is constructed using information from Table 7 and Table 4 (steps shown in Appendix B). In this case, there are no transitivities to be removed; hence we retain the graph shown in Figure 3. It is to be noted that this "model" emerged from the data as it were as opposed to us framing the relationships in any predefined manner.

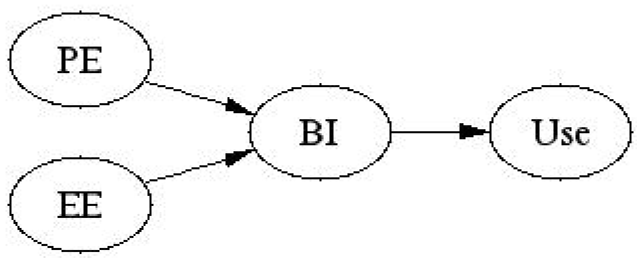

Figure 3. Final Influence Structure

Given the contextual relationship (*influences*), we can read this diagram to convey the following: performance expectancy (PE) and effort expectancy (EE) influence behavioral intention (BI), which influences IS use (Use). While Figure 3 shows the consensus structure, it is important to keep in mind that there are 88 (number of respondents) possible graphs.

5. DISCUSSION

The key objective of this paper was to show how a non-directed and qualitative approach could be used to replicate results from a validated line of research. The final result in Figure 3 shows that the model that emerges from the ISM process is structurally identical to the one suggested by Davis (1989). The primary contribution of this research paper lies in demonstrating that ISM is an efficient and effective method to undertake research that is aimed at theory development based on an inductive approach. In the remainder of this section, we discuss the scientific contributions and implications, practical implications, and limitations of our work.

The structure of equations, variables, and parameters of module is visualized by the ISM hierarchy (Warfield 1976). Since the directed graph consisting of extracted linkages does not explain the whole systematic order of cause-effect relationships, a researcher may not be able to grasp how to calculate an output variable from other input variables and parameters. The structural analysis by ISM classifies variables and parameters according to the hierarchical levels, which are obtained by finding a set of nodes that cannot reach any other nodes except the set itself. The hierarchically organized directed graph ensures that only linkages from a lower level to an upper level are included in the entire graph; however there is no reverse directional arc. Nodes at the same level tend to imply that they codetermine or co-influence elements in the subsequent level.

An important part of the entire exercise needs to be underscored at this stage. There was no a priori definition of a dependent variable. Nor was there any a priori definition of an independent variable. However, as argued by Bougon and Weick (1977), who used a variant of this technique as causal maps, the variables on the left, middle and right can be treated as the set of givens, means and ends respectively. As a result, such a model, once it emerges from research, can subsequently be subjected to further empirical scrutiny by subjecting each element pair to tests of correlations individually or using structural equation modeling or path analysis.

It is also important to note from our data collection and analysis process that we have provided a robust framework for stepwise refinement and synthesis. Both the ability to do stepwise refinement and synthesize multiple inputs are important for inductive research. Stepwise refinement is important from the standpoint of localized attention to a specific phenomenon at any given point in time. When a respondent deals with pairs of constructs, it is hoped that she is concentrating on those two constructs only (and operationalizing the *ceteris paribus* assumption). The essential idea is to build a larger conceptual model piece by piece. Two types of synthesis have also been demonstrated in this paper. The first is the synthesis of pair-wise information into a larger graph and the second type of synthesis is the aggregation of multiple respondents' viewpoints into a single graph.

Depending on the nature of the contextual relationship, the derived ISM can be considered to be a causal graph or a causal structure. In this study, given the contextual relationship that we have chosen ("*influences"*), it would be appropriate to consider the emergent graph as a causal model. However, in case we had used "is more important than" as the contextual relation, then the emergent graph would be more meaningful as a priority structure and it would not be even appropriate to consider it to be a causal structure. This is a framework that allows qualitative research to be efficiently replicated. One of the major challenges of qualitative research is that it often has a significant interpretive component. Here the interpretation is left almost entirely to the respondent and the researcher can focus on addressing the rigor of the research protocol.

Like other methodologies, ISM too has its weaknesses. One weakness of this approach includes respondent fatigue. We have found that comparing 36 pairs of elements got the respondents bored – especially toward the later stages of the pair-wise comparison process. In addition, some respondents could not really shut out other elements while dealing with a specific element pair. For instance, a respondent, while comparing PE and EE stated that PE influences EE and her explanation was that "I find the spreadsheet easy to use because I use it a lot; and I use it a lot because it improves my job performance." While collecting data, we tended to avoid "educating" the respondent in real-time and "contaminating" the data.

It is also natural for other researchers to question the validity of this approach and, in particular, question the relevance of the cut-off value of 50%. Our argument is that if at least fifty percent of respondents agree on something, then there is something of significance there. Just as in the case of p-values (probability of making a type I error) in inferential statistics, if researchers want additional stringency they can reduce the alpha value (maximum allowable type-I error) from 0.05 to 0.01, we could, in our case, increase the threshold to 60 or even 70 percent. However, we have found that it is revealing for the researcher to start with a lower threshold and incrementally increase the threshold to unravel more resilient graph or causal structures.

A third weakness of this approach, as it has been presented here, is that there is no mention of the strength of the relationships between variables. However, there are multiple resolution frameworks for this problem. In the context of causal or influence maps, there are many approaches that can be used to impute the strength of the causal or relational connection. Techniques like social networks and matrix algebra (Axelrod, 1976; Carley and Palmquist, 1992), system dynamics (Eden et al., 1992), relation algebra (Chaib-Draa, 2002), neural networks (Rossi et al., 1983), and Bayesian probabilities (Nadkarni and Shenoy, 2004) have been used.

We feel that IS researchers adopting an emic stance to IS research can use this approach to complement traditional research approaches. An *emic* analysis of phenomenon is based on internal structural or functional elements of a particular cultural or organizational system. An *etic* analysis is based on predetermined general concepts external to that cultural system (Lovelace, 1984). Since, we have adopted an *emic* perspective that provides the "insider's" or "native's" interpretation of or "reasons" for his or her customs/beliefs, this specific perspective can and should be used to compare and contrast with the *etic* perspective which is the external researcher's interpretation of the same beliefs or relationships. In other words, this approach can be very useful to compare an IS practitioner's (user's or manager's) mental models from what things mean from an analytical, anthropological perspective.

It would be pertinent to point out at this stage that ISM, as a research approach, may have appeared to be overkill when dealing with four variables. We need to keep in mind that our purpose was to demonstrate the efficacy of ISM. Needless to say, ISM is far more effective when a researcher is confronted with a large number of variables (maybe 10 or more) and where causal ambiguities are a result of the novelty of the phenomenon or the inherent complexities.

Finally, the method, as explained in this study, may not appear as inductive as suggested in the introduction. This is because, it may seem that ISM can only be used to generate models of which the elements are already known. ISM, as shown here, is capable of generating the relationships between the elements. In order to elicit a shared mental model, a variant of the approach presented here, would work better. This would involve a two-step approach in which first the elements are collected followed by the relationships. This is the suggested approach for researchers planning to adopt this approach.

6. CONCLUSIONS

In this study, we were able to show that a qualitative, open-ended and respondent-driven approach successfully generated a well-accepted model (theory). The main implication for researchers is that the use of such approaches can form an extremely effective and efficient method for capturing the shared mental models of IS practitioners. It allows IS researchers to perform research that is interpretive and grounded in data efficiently. This is important because, in many instances, IS phenomena are so dynamic and changes occur so fast in the IS domain that it is unreasonable to expect researchers to study stable phenomena and replicate or disconfirm results obtained by other researchers. Moreover, what happens in the field, more often than not, drives academic IS research – and not the other way round. Hence, it is important to employ methodologies like ISM that efficiently allow the capture and synthesis of practitioners' viewpoints. From a practical perspective this approach is even more valuable because this approach is context sensitive and can be replicated effectively by researchers across contexts. By using ISM we have been able to "focus on the concerns of practice, provide real value to [IS] professionals Benbasat and Zmud (1999, p. 5)" and apply a balance of pragmatic and academic tone.

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Appendix A

	Performance expectancy	**Effort expectancy**	**Social influence**	**Facilitating conditions**	**Behavioral intention**	**Use behavior**	**Self-efficacy**	**Anxiety**	**IT-enabled productivity**
Performance expectancy		1	2	3	4	5	6	7	8
Effort expectancy			9	10	11	12	13	14	15
Social influence				16	17	18	19	20	21
Facilitating conditions					22	23	24	25	26
Behavioral intention						27	28	29	30
Use behavior							31	32	33
Self-efficacy								34	35
Anxiety									36
IT-enabled productivity									

This table shows the overall data collection framework. Users were requested to fill in this table with ⇙, ⇗ or O based on the protocol explained in the body of the paper. Cells that are shaded darker (cell numbers 1, 2, 4, 5, 9, 11, 12 and 27) have been used for analysis in this paper. The cell numbers were used by the respondents and interviewers to link their responses with justifications for those responses.

Appendix B

The following steps outline how the interpretive structural modeling methodology is implemented:

i) ***Identify elements***: The elements of the system are identified and listed. This may be achieved through past research, brain storming, or using the nominal group technique.

ii) ***Establish a contextual relationship:*** A contextual relationship between elements is established, depending upon the objective of the modeling exercise. This is a verb or verb phrase like "increases" or ""is more important than" or "leads to."

iii) ***Prepare a reachability Matrix:*** For the contextual relation from element E_i to E_j, but not in the reverse direction, then element $E_{ij} = 1$ and $E_{ji} = 0$ in RM. For the contextual relation from E_j to E_i, but not in the reverse direction, then element $E_{ij} = 0$ and $E_{ji} = 1$ in RM. For an interrelation between E_i and E_j (both directions), then element $E_{ij} = 1$ and $E_{ji} = 1$ in RM
To represent that E_i and E_j are unrelated, then element $E_{ij} = 0$ and $E_{ji} = 0$ in RM.

iv) ***Perform level partitioning:*** Level partitioning is done in order to classify the elements into different levels of the ISM structure. For this purpose, two sets are associated with each element E_i of the system - A *Reachability Set* (R_i) that is a set of all elements that can be reached from the element E_i, and an *Antecedent Set* (A_i), that is a set of all elements that element E_i can be reached by. In the first iteration, all elements, for which $R_i = R_i \cap A_i$, are Level I Elements. In successive iterations, the elements identified as level elements in the previous iterations are deleted, and new elements are selected for successive levels using the same rule. Accordingly, all the elements of the system are grouped into different levels.

v) ***Develop canonical matrix:*** grouping together elements in the same level develops this matrix. The resultant matrix has most of its upper triangular elements as 0, and lower triangular elements as 1. This matrix is then used to prepare a Digraph.

vi) ***Draw the digraph:*** Digraph is a term derived from **Di**rectional **Graph**, and as the name suggests, is a graphical representation of the elements, their directed relationships, and hierarchical levels. The initial digraph is prepared on the basis of the canonical matrix. This is then pruned by removing all transitivities, to form a final digraph.

vii) ***Create the interpretive structural model:*** The ISM is generated by replacing all element numbers with the actual element description. The ISM therefore, gives a very clear picture of the system of elements, and their flow of relationships.