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AGGREGATED CAUSAL MAPS: AN APPROACH TO ELICIT AND AGGREGATE THE KNOWLEDGE OF MULTIPLE EXPERTS

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ABSTRACT

This paper presents a systematic procedure to elicit and aggregate the knowledge of multiple individual experts and represent it in the form of an Aggregated Causal Map (ACM). This procedure differs from existing methods in two ways. First, unlike other methods, this method does not rely on group interaction in eliciting knowledge of multiple experts, and, therefore, is not fraught with biases associated with group dynamics. Second, this method uses both the idiographic and nomothetic approaches while existing methods focus on nomothetic approaches to knowledge elicitation. We draw on the strengths of both approaches by using the idiographic approach to elicit and aggregate the knowledge of multiple experts and the nomothetic approach to validate the knowledge elicited. We illustrate the procedure by constructing the ACM of eight key decision makers about an enterprise system adoption decision.

Keywords: causal maps, nomothetic versus idiographic approaches, knowledge elicitation and aggregation

I. INTRODUCTION

Eliciting knowledge from multiple domain experts in developing knowledge-based systems is becoming increasingly important [Rush and Wallace, 1997; Turban and Tan, 1993]. The notion that "all you need to build an expert system is one domain expert" does not apply to complex and varied domains, such as financial analysis and information systems management, where any given expert is often knowledgeable in only a small subset of the tasks in the domain [O'Leary, 1998; McDermott, 1981; Mittal and Dym, 1985; Smith and Baker, 1983]. Consequently, representation of complex domains requires knowledge of multiple experts specializing in different sub-areas of the domain.

Ample techniques for eliciting and representing knowledge of multiple experts were developed in the field of knowledge engineering [Massey and Wallace, 1991; Alexander and Evans, 1988]. The majority of these techniques, however, depend upon the use of groups to pool the knowledge of

multiple experts. These methods are therefore fraught with the biases resulting from group dynamics [Shaw, 1971] and the problems associated with group process losses (e.g., conformance pressure) [Steiner, 1972]. Methods that allow knowledge engineers to elicit knowledge of multiple experts individually, and then aggregate it using systematic techniques are sparse [Rush and Wallace, 1997].

In addition, most techniques that allow aggregating knowledge collected from individual experts focus primarily on nomothetic methods to elicit causal knowledge of experts [e.g., Rush and Wallace, 1997; Steier et al., 1993]. Nomothetic approaches are aimed at confirming widely accepted, existing knowledge of a specific domain using structured methods, rather than eliciting the subjective and unique knowledge of the experts using unstructured methods [Tan and Hunter, 2002]. Although nomothetic methods are useful in eliciting knowledge about known and well-developed domains, they are not appropriate for emerging domains where very little 'widely accepted body of knowledge' exists. In such new and emerging domains, an idiographic approach may be more appropriate for eliciting knowledge as it allows knowledge to be elicited in linguistically distinct ways (typically through unstructured or semi-structured elicitation procedures) and is not bound by predefined variables. The primary purpose of the idiographic approach is to capture unique, subjective knowledge of individual experts using in-depth interviews conducted with experts, thereby minimizing biases imposed by the modeler [Eden and Ackermann, 1998]. The expert knowledge elicited through the idiographic approach can be validated using nomothetic methods, which refer to highly structured methods such as predetermined questions to which the experts will respond.

In this study, we propose a systematic procedure that integrates both the idiographic and nomothetic approaches in eliciting, aggregating and validating the knowledge of individual experts. We use the idiographic approach to elicit and aggregate the knowledge of multiple experts and the nomothetic approach to validate the knowledge elicited from the experts. By integrating idiographic and nomothetic methods, we attempt to combine the strengths of both approaches and reduce the limitations of either. We note, however, that the methodology proposed herein is not intended to replace the previously developed techniques. Rather, it is intended to supplement existing methods or to serve as another tool at the disposal of the knowledge engineer.

We propose a five-step procedure to aggregate the knowledge of multiple experts using the causal mapping technique. Causal mapping is a technique that is used to elicit and represent domain knowledge of experts in the form of a graphical network called a causal map. A causal map (also called an influence diagram or a cause map) is a directed graph in which causal concepts (or nodes) represent the important variables that make up a domain. Causal connections are the directed arrows that connect these concepts to represent causal relationships between the variables. The steps are as follows:

1. Elicit knowledge of individual experts using exploratory interviews.
2. Conduct a textual analysis of the interviews to represent the knowledge of individual experts as causal maps.
3. Aggregate the individual causal maps into an aggregated causal map (ACM) using network analytic methods.
4. Use nomothetic methods to validate the ACM of experts, and
5. Derive the parameters of the causal map using probabilistic coding techniques.

In Section II, we review the relevant literature on elicitation and aggregation of knowledge from multiple experts, and explain why causal mapping is an appropriate technique for representing domain knowledge. In Section III, we elucidate the meaning and components of a causal map. In Section IV, we describe our proposed method of constructing ACMs and in Section V we illustrate

the method by constructing an ACM of the key decision makers of an enterprise resource planning adoption decision. In the final section, we discuss the implications and limitations of the ACM approach, and offer directions for future research.

II. KNOWLEDGE ELICITATION METHODS FROM MULTIPLE EXPERTS

KNOWLEDGE ELICITATION FROM MULTIPLE EXPERTS

A considerable research deals with how to elicit and represent knowledge from multiple experts for use in a decision support or knowledge-based system. This stream of research is primarily motivated by an increasing need for using multiple experts in complex decision situations. Rush and Wallace [1997] and Turban and Tan [1993] summarize the benefits of using multiple experts as follows (also see [Medsker et al., 1995; Moore and Miles, 1991; McGraw and Seale, 1988]):

- On average, a group of experts will make fewer mistakes than single experts.
- Several experts in a group can often reduce or eliminate the need for a world-class expert (who is often expensive and difficult to obtain).
- The collective expertise of multiple experts will often be both broader and deeper than that of a single expert.
- Often, the simultaneous consideration of the thoughts of multiple experts will result in deeper insight into the problem at hand.

Alexander and Evans [1988] describe several general methodologies for integrating knowledge from multiple experts. Consensus methods—such as nominal group technique and brainstorming—use groups as a means for reaching agreement among experts on how the problem situation should be structured and/or addressed. Blackboard systems decompose the problem situation into components and then assign each component to the group of experts most qualified to address it. Other methods include specific lines of reasoning [LaSalle and Medsker, 1991] and automated knowledge elicitation techniques.

Most of the existing approaches use some form of group interaction to elicit knowledge of multiple experts. Group interactions are useful in exploiting synergies in expert knowledge and enhancing collaborative learning among experts by exposing them to divergent problem solving approaches [Steiner, 1972; Nunamaker et al., 1991]. Thus, group elicitation techniques encourage shared meaning construction of the problem situations and a joint commitment to shared goals and shared diagnosis and monitoring of activities. However, approaches that rely heavily on group interaction are open to biases resulting from group dynamics or problems in group decision making [Nah et al., 1999; Rush and Wallace, 1997; Shaw, 1971; Steiner, 1972; Turban, 1992; Turban and Aronson, 1998] including:

- Groupthink phenomena
- Fear on the part of some domain experts of disagreements with senior experts or a supervisor
- Conflict of opinions among multiple experts leading to a compromise solution
- Waste of time in group meetings
- Difficulties in scheduling meetings among multiple experts
- Cognitive inertia where discussions move along one or a limited train of thought
- Social loafing where some experts may not contribute to the group process

- Group polarization where group opinions become more extreme and biased
- The negative impact of experts who dominate during group interactions. By exerting control, these experts may inhibit the full participation of other experts in the group. Such a phenomenon precludes the group from performing at its full potential. The Delphi technique was developed by Dalkey and Helmer [1963] in response to this problem.

To avoid these biases and problems, techniques of eliciting knowledge from multiple experts that do not rely on group interactions need to be developed. However, such approaches for eliciting and aggregating expert knowledge are rare [Deing et al., 1992; Rush and Wallace, 1997, Steier et al., 1993].

IDIOPHGRAPHIC AND NOMOTHETIC APPROACHES TO ELICITATION OF KNOWLEDGE

As discussed in Section I, two major approaches are salient in the knowledge elicitation literature: idiographic and nomothetic [Carley and Pamliquist, 1992; Eden and Ackermann, 1998]. The idiographic approach to knowledge elicitation is unstructured, open-ended and context-specific whereas the nomothetic approach is structured and draws on pre-determined and generalized concepts for comparison and confirmatory purposes. Hence, the idiographic approach is more suited for ill-structured and unfamiliar domains whereas the nomothetic approach is more appropriate for well-defined and familiar domains.

A comparison of idiographic and nomothetic methods of knowledge elicitation is shown in Table 1. The purpose of nomothetic approaches is to confirm *a priori* determined, widely accepted and generalized assumptions relating to a specific domain by answering the question: “Does the expert knowledge contain what I expect it to contain?” On the other hand, the purpose of an idiographic approach is to explore a new or unfamiliar domain inductively by posing the question: “What does the expert knowledge contain?” In a nomothetic approach, the domain concepts (e.g., variables, attributes) are defined *a priori* and these concepts are imposed on the data elicited, whereas in the idiographic approach, the domain concepts emerge from the responses of the experts. Unlike the generalized and context-free concepts yielded by the nomothetic approach, the emergent concepts in the idiographic approach are unique and more context-specific. The idiographic approach “focuses on the subjective experiences of the individual and presents results in expressions and terms used by the individual” (p.51) whereas the nomothetic approach “necessitates the use of a common set of elements and/or constructs to permit comparisons to be made.” (p.52) [Tan and Hunter, 2002]

Table 1. Comparison of Idiographic and Nomothetic Methods of Knowledge Elicitation

	Idiographic Approach	Nomothetic Approach
1. Basic Question Addressed:	“What does the expert knowledge contain?”	“Does the expert knowledge contain what I expect it to contain?”
2. Data Elicitation Techniques Employed:	Unstructured techniques: in-depth interviews with open-ended questions, secondary documents such as speeches, reports, etc.	Structured techniques: structured interviews, visual card sorting, influence diagrams, means-ends analysis
3. Suitability:	Suitable for ill-defined and unfamiliar domains	Suitable for well-defined and familiar domains
4. Type of Knowledge Captured:	Both declarative and procedural domain knowledge of experts	Primarily declarative or generalized domain knowledge of experts

Idiographic approaches use qualitative and inductive techniques such as in-depth interviews involving open-ended questions. On the other hand, nomothetic methods employ intrusive and

structured techniques of data elicitation such as influence diagrams, means-ends analysis, and visual card sorting. A major consideration in the choice of the knowledge elicitation approach is the domain being investigated. For example, the nomothetic approach is more suitable for clearly defined and familiar domains, whereas the idiographic approach is useful for ill-defined and complex domains.

Finally, the two approaches also differ in the type of knowledge elicited. Expert knowledge based on a nomothetic approach represents a greater degree of generalized and factual knowledge (also called declarative knowledge) of subjects about the domain being evaluated. On the other hand, expert knowledge elicited through an idiographic approach represents both declarative and procedural knowledge of experts. Procedural knowledge represents implicit and explicit procedures used by experts to perform a given task. Procedural knowledge can tell us a great deal about the structure of a given task and the repertoire of procedures that an expert can draw upon as (s)he engages in it. In other words, an idiographic approach yields a richer understanding of the processes that individuals use in decision-making and helps gather important insights into the general domain knowledge of individuals.

Most of the systematic techniques for knowledge elicitation apply the nomothetic methods to elicit expert knowledge and they do not address the validation issues involved in elicitation and aggregation of expert knowledge. For example, in the MEID method [Rush and Wallace, 1997], subjects were provided with a detailed decision case (Oil Wildcatter) with relevant pre-defined variables and asked to draw an influence diagram, whereas in the SOAR method [Steier et al., 1993], experts were provided with decision constraints and asked to use their knowledge to evaluate each constraint.

Nomothetic methods are intrusive in nature because the list of relevant variables making up a domain is determined in advanced by the modelers [Carley and Palmquist, 1992; Eden and Ackermann, 1998]. Hence, the nomothetic methods may not capture the domain knowledge of experts comprehensively. Comprehensiveness is especially important for large, varied and complex decision domains such as information systems management issues concerning enterprise resource planning adoption, strategic alignment of IT/IS with business goals, and requirements analysis for information systems development. These domains require the knowledge of experts from diverse areas including technical experts, functional experts, management, and users or customers. Studies indicate that an idiographic approach is better suited to capture the diverse knowledge of multiple domain experts comprehensively [Carley and Palmquist, 1992; Huff, 1990]. Other benefits of an idiographic approach include [Carley and Palmquist, 1992]:

- In comparison with hypothetical cases or pure attribute lists employed in nomothetic techniques, elicitation in an idiographic approach is based on real cases that are meaningful to the expert, which improve the meaningfulness of the response elicited.
- Elicitation of the initial pool of variables and the relations among these variables through an idiographic approach is relatively unobtrusive and less susceptible to modeler bias than direct questions used in the nomothetic approach.
- The mere act of explicating and formalizing tacit knowledge of experts through an idiographic approach surfaces hidden assumptions, which can then be scrutinized [Carley and Palmquist, 1992]. The tacit knowledge can help experts apply their domain knowledge more effectively in different decision situations [Hodgkinson et al., 1999].

In our proposed procedure, we use an idiographic approach to capture the knowledge of experts and nomothetic methods to validate the knowledge. The ACM procedure proposed in this paper is well suited for capturing the generic as well as specialized knowledge of multiple experts with diverse backgrounds.

Summarized below are some other benefits of using the ACM method over other existing methods for eliciting knowledge of multiple experts:

- It uses an idiographic approach to pool rich knowledge of experts and can be applied to complex and emerging domains where hard data is difficult to obtain and boundaries of the domains are not clearly defined.
- It captures causal knowledge of multiple experts about a domain that other methods such as protocol analysis and repertory grids were not designed to capture. Causal knowledge of experts is important because domain knowledge is described and understood through causal connections [Huff, 1990].
- The causal mapping technique, on which our method is based, is more comprehensive, less time-consuming and causes lesser inconvenience to experts during knowledge elicitation than other techniques such as protocol analysis and repertory grids [Brown, 1992].
- It does not rely on group interaction to capture knowledge of multiple experts. Knowledge of individual experts can be captured and represented separately, and a composite causal map of their aggregated knowledge can be systematically generated from these individual maps.
- It provides flexibility in the use of different types of quantitative analyses such as neural networks [Wang, 1996], system dynamics [Forrester, 1961] and Bayesian networks [Nadkarni and Shenoy, 2001] that are typically employed to analyze individual level causal maps.
- It controls for biases that may arise from the use of idiographic methods by validating the domain knowledge of experts using nomothetic methods of knowledge elicitation.

III. CAUSAL MAPPING

Causal maps are directed graphs that represent the cause-effect relations embedded in the experts' thinking. Eden et al. [1992] define a causal map as a "directed graph characterized by a hierarchical structure which is most often in the form of a means/end graph." Causal maps express the judgment that certain events or actions will lead to particular outcomes. The three major components of a causal map are:

- causal concept,
- causal connection and
- causal value.
-

Figure 1 shows a part of a causal map of an informed buyer relating to a home purchase decision. The buyer conducted extensive real estate research and visited a number of different homes in different areas of the town and, therefore, possesses the knowledge of an 'expert buyer.'

Causal concept. A causal concept is a single ideational category [Carley and Palmquist, 1992]. A causal concept can be an attribute, issue, factor or variable of a domain, and is represented by a node in the causal map. A concept can be a single word such as 'Size,' or 'Price;' composite words such as 'Mortgage Rate,' 'Favorable Financing,' and 'Convenient Location;' or a more complex phrase such as 'Percentage Down Payment,' 'Age of the House,' 'Favorable Home Features,' 'Number of Bedrooms,' and 'Buy the House'.

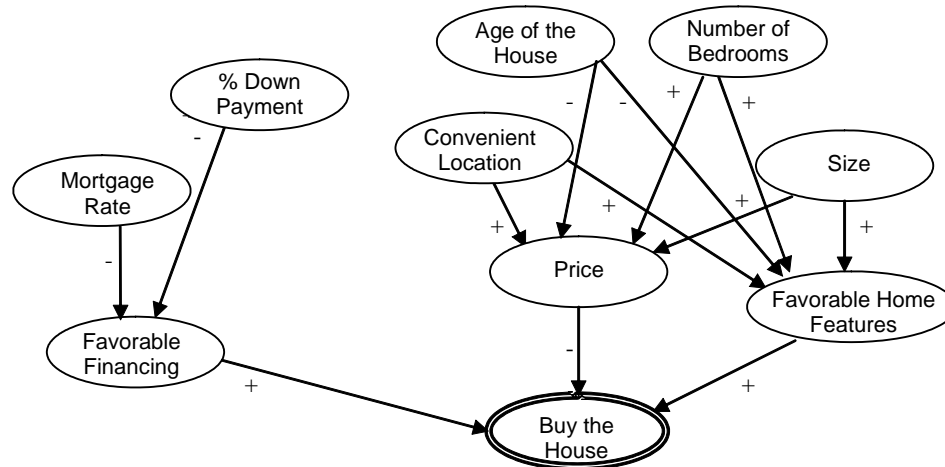


Figure 1. Causal Map of a Prospective Buyer in a Home Purchase Decision

CAUSAL CONNECTION

A causal connection is a tie that links two concepts in a map and is represented with a unidirectional arrow. It depicts an antecedent-consequence relationship between two concepts. The concept at the tail of an arrow is taken to cause the concept at the head of the arrow. In Figure 1, 'Mortgage Rate' and 'Percentage Down Payment' lead to 'Favorable (or unfavorable) Financing,' whereas 'Age of the House,' 'Number of Bedrooms,' 'Size,' and 'Convenient Location' result in 'Favorable (or unfavorable) Home Features.' Moreover the four antecedents of 'Favorable Home Features' also determine the 'Price' of the House. A causal connection can be positive or negative. A positive connection indicates that an increase in the causal concept leads to an increase in the effect concept, whereas a negative connection indicates that an increase in the causal concepts leads to a decrease in the effect concept. In Figure 1, for example, 'Number of Bedrooms' and 'Size' exert a positive influence on the 'Price' of the house. Thus, the greater the number of bedrooms and the larger the size of the house, the higher the price of the house. On the other hand, 'Age of the House' creates a negative influence on both 'Price of the House' and 'Favorable Home Features.' Thus the older the house, the lower the price of the house and the lower the chance that the buyer views the features of this house as favorable.

CAUSAL VALUE

A causal value represents the strength of the causal connection. Different techniques have been used to determine the causal value including social networks and matrix algebra [Carley and Palmquist, 1992], neural networks [Wang, 1996], system dynamics [Forrester, 1961] and Bayesian networks [Nadkarni and Shenoy, 2001]. The choice of techniques used to determine the causal value is determined by the purpose of analysis. Although this paper focuses on the procedure to aggregate the graphical structure of causal maps, we extend the individual-level probabilistic encoding technique [Nadkarni and Shenoy, 2001] to the group level. We also address key issues in the aggregation of individual causal values including rules of aggregation and resolution of disagreements across experts. These issues of aggregation are important in most quantitative analyses used in causal maps. A detailed discussion of different quantitative analyses used in causal maps can be found in the papers cited above.

IV. PROCEDURE FOR CONSTRUCTING AN AGGREGATED CAUSAL MAP

Using causal mapping, we propose a systematic procedure to construct the aggregated causal maps (ACMs) based on the qualitative knowledge of multiple experts. As described in Section 1, this procedure consists of five main steps:

Step	What is done
1. Data elicitation	Individual experts are interviewed using qualitative interviews to elicit their domain knowledge and the experts' responses to the interviews are transcribed to get a text that we call a 'narrative.'
2. Derivation of individual causal maps	The narrative obtained in the first step is analyzed using a systematic content analysis technique to derive the graphical structure of the causal maps—consisting of causal concepts and causal links—of each expert.
3. Aggregation of individual causal maps	The graphical structures of individual causal maps are aggregated into an ACM using network analytic methods.
4. Validation of structure of aggregated causal map	The graphical structure of the ACM is validated using nomothetic methods.
5. Derivation of causal values of aggregated causal map	The causal values associated with the links in the ACM are derived using probabilistic encoding techniques.

DATA ELICITATION

In this step, interviews are conducted with experts using an idiographic approach to collect domain information from them. In-depth qualitative and open-ended questions are posed to the expert to obtain raw data in the form of a narrative. This narrative is then used to construct causal maps using textual analysis. Unstructured interviews are most appropriate for eliciting expert knowledge because they are relatively less intrusive in eliciting the expert knowledge. The concepts and the links between concepts are allowed to emerge in the process of interviews by sequencing the interview questions based on the responses of the expert. These methods are particularly suitable for eliciting expert knowledge for complex and ill-structured domains. A widely used qualitative interview technique that elicits a narrative is an open interview with probes [Rossi et al., 1983], which consists of three different types of questions:

- broad (open-ended) questions,
- probing questions, and
- closed questions.

The sidebar presents an example of an open interview with probes conducted with a prospective buyer relating to the decision of whether or not to buy the house at 840 Royal Blvd. The interview started by posing a broad, open-ended question to extract the general knowledge of the subject about a domain such as "What factors would you consider in deciding whether or not to buy the house at 840 Royal Blvd.?" The answer to this question can then be used to identify 'probes' or key phrases for follow-up questions. Subsequent questions presented to the subject relate to each of these probes in terms of direct questions as well as indirect relationships with other probes offered by the subject. In contrast to open-ended questions, closed questions are specific and require the subject to answer either 'yes' or 'no.' Closed questions are used primarily for clarification purposes.

An Example of Interview with Probes

Question 1: What factors would you consider in deciding whether or not to buy the house at 840 Royal Blvd.?

Prospective Buyer's response: I would consider **features of the house, how favorable the financing is, and price of the house...**

Question 2: You mentioned **features of the house**. What specific features of the house are most relevant to your decision to buy a house?

Prospective Buyer's response: **Convenient location** is definitely important... Other features that are important to me are **number of bedrooms, size and age of the house...**

Question 3: What aspects of **financing** are relevant to your decision?

Prospective Buyer's response: ...things such as the **percentage of the down payment** I have to make and the **mortgage rate...**

The bold phrases in the prospective buyer's response shown in the sidebar represent the probes identified by the interviewer. For example, "features of the house" is a probe that was used by the interviewer to obtain more detailed factors that made up features of the house. This probing question (question 2) yielded 4 additional probes: "convenient location", "number of bedrooms", "size", and "age of the house." Additional questions were posed to the subject to obtain more detailed information about each of these probes. This probing continues until the subject exhausts the list of factors that made up the domain and cannot think of any additional factors.

The responses of the subject to the open interview can be transcribed to yield a 'narrative' or a 'text.' This narrative or text is then analyzed using a systematic procedure of textual analysis to derive causal maps.

DERIVATION OF INDIVIDUAL CAUSAL MAPS

Four steps are used to construct the causal maps. The steps are based on the narrative derived from the unstructured interviews by using textual analysis [Axelrod, 1976]. These steps are illustrated in Figure 2.

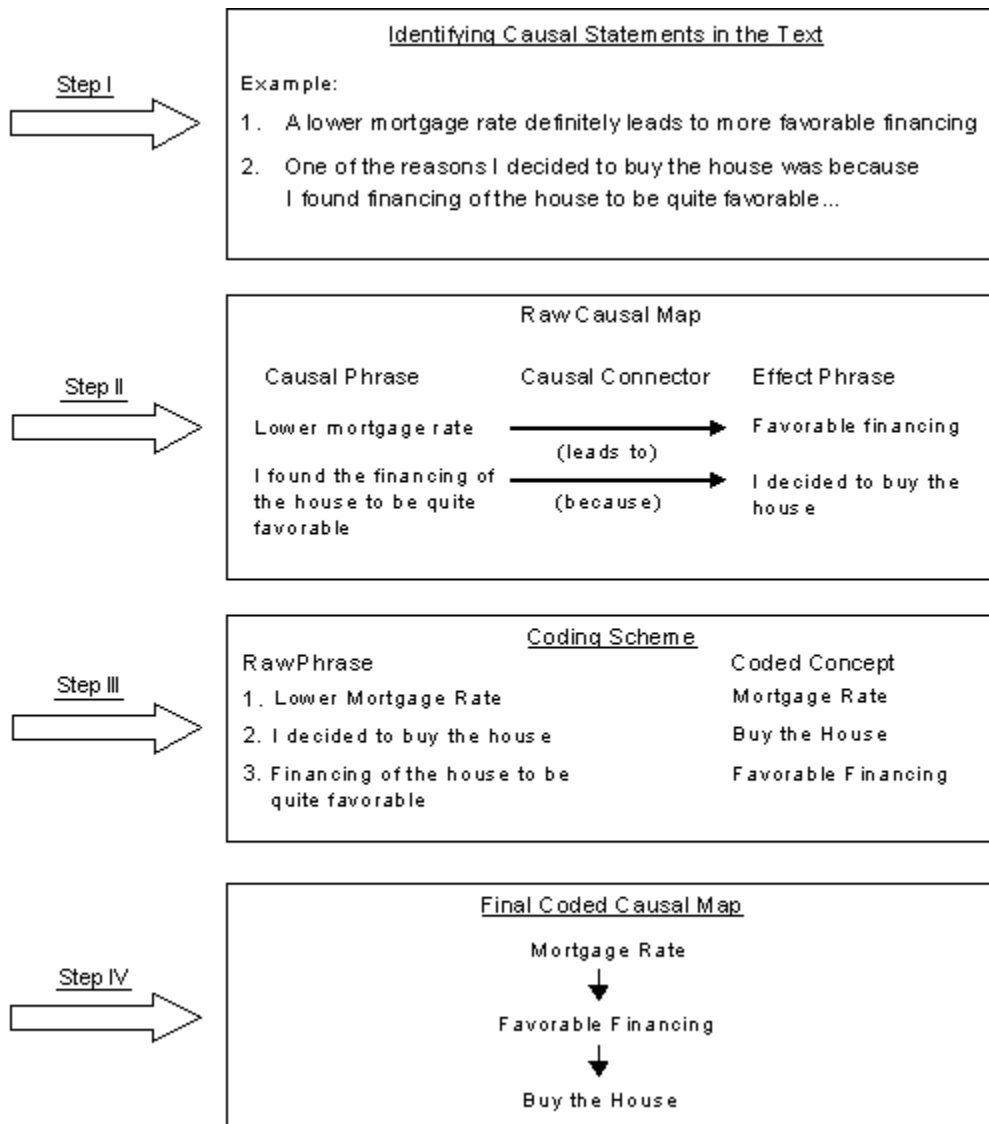


Figure 2. Example of Procedure for Deriving Individual Causal Maps

1. Identify Causal Statements in the Narrative.

The first step is to identify causal statements in the narrative. Causal statements are statements in the narrative that explicitly contain a cause-effect relationship. A causal statement links two different concepts through a causal connector. An important consideration in identifying causal statements in a narrative is to define rules for recognizing causal connectors. This definition involves developing a comprehensive dictionary of words or phrases that can be considered as causal connectors. Examples of words used to represent causal connectors include 'if-then', 'because', 'so,' 'as,' and 'therefore'. Each statement containing a causal connector can be identified as a 'causal statement.' This task can be performed manually or can be automated.

In the manual procedure, knowledge engineers can develop a comprehensive dictionary of causal connectors before going through the narrative or the text yielded by the open interview. They can then recognize the causal connectors in the narrative to identify causal statements. The advantage of the manual procedure is that raters can add new causal connectors to the pre-defined list of causal connectors while going through the narrative and hence the chance of missing a causal statement is low. But at the same time, the manual procedure is labor intensive and time consuming. Figure 2 shows two causal statements contained in the narrative of a prospective buyer relating to the decision of buying a house. These statements were identified as causal statements because they contain words listed as causal connectors ('leads to' and 'because').

In the automated process, a computer program can be created to recognize the causal connectors in the narrative. The automated process is neither time consuming nor labor intensive, but it does not provide the flexibility to add new causal words to the pre-defined list of causal connectors. Also, certain uniquely phrased sentences that do not contain causal connectors but imply causality may be lost in the automated procedure. The choice of manual versus automated process may be determined by factors such as nature of the domain being investigated, length of the narratives, and the number of experts. For example, a manual procedure may be appropriate for eliciting knowledge relating to a fairly unique and complex domain whereas an automated process may adequately capture expert knowledge relating to a well-defined domain. Similarly, a manual procedure would be appropriate for identifying causal statements in short narratives of a small number of domain experts. However, a manual procedure may not be feasible for long narratives of a large number of domain experts. In the latter case, an automated program is more efficient.

2. Construct Raw Causal Maps

Once the causal statements are identified, they are broken into causal phrases, causal connectors and effect phrases to derive the raw causal maps. Step III in Figure 2 shows how the two causal statements are broken into raw causal maps. Again these maps can be created manually or the process can be automated using computer programs. However, clear rules for identifying causal phrases and effect phrases need to be defined for each causal connector. For example, in Figure 2, the rule for identifying cause and effect phrases for the causal connector 'leads to' is very different from the rule for the causal connector 'because.' The phrase before 'leads to' is a causal phrase whereas the phrase before 'because' is an effect phrase. Care must be taken to ensure that the direction of causality is properly coded.

3. Design Coding Scheme

The raw causal maps derived in the previous step are cast in the language of the expert. In spite of their usefulness, the raw maps obscure analysis because of their complexity and because of variations in the way the same ideas may be phrased. Hence there is a need to design a coding scheme to recast the raw causal maps into the final causal maps. This process of coding is called filtering. Filtering is the process of determining which part of the text to code, and what words to use in the coding scheme. In filtering, similar phrases in the raw causal maps are

grouped into a single coded concept. Filtering can be used to move the coded text beyond explicitly articulated ideas to implied or tacit ideas, and to avoid misclassifications of concepts due to peculiar wording on the part of individuals. The experts whose causal maps are being developed should be closely consulted while developing the coded concepts to ensure that the coded concepts do not change the meaning of the raw phrases.

4. Convert Raw Causal Maps into Coded Causal Maps

Finally, the coding scheme developed in Step III is used to recast the raw causal maps into coded maps (Step IV). A coded causal map is a network of concepts formed from causal statements in a narrative depicting directionality (cause-effect) and sign (positive and negative) of the relationships between the concepts. Two statements are linked if they share at least one concept. For example, causal statement 1 and causal statement 2 in Figure 2 share the concept "Favorable Financing" thus resulting in the network of "Mortgage Rate → Favorable Financing → Buy the House."

The final coded map can be constructed using a computer program such as Netanalysis [Narayanan, 1995], CODEMAP [Carley and Palmquist, 1992], *Decision Explorer* [2003] and UCI net [2002]. The Netanalysis program links pairs of concepts with their common concepts to provide a network of concepts and the relationships between them. It provides output in the form of matrices that contain the direction and sign of the links between concepts. Programs such as UCI net and CODEMAP provide output in the form of graphs that show the domain variables in the form of nodes and display the direction and sign of the links between these nodes.

AGGREGATION OF INDIVIDUAL CAUSAL MAPS

Individual causal maps of domain experts can be combined into aggregated causal maps. Such aggregation allows an integration of the diverse knowledge of multiple experts and captures the concepts and links representing a specific domain comprehensively.

Individual causal maps are aggregated using a two-step procedure in which causal maps are represented as matrices and these individual matrices are added to combine the causal maps [Eden et al., 1992]. First, an individual causal map is represented in the form of a matrix called an adjacency matrix, where columns are causes and rows are effects. A '0' (no relation), '+' (positive relation) or a '-' (negative relation) is entered in each corresponding cell of the adjacency matrix to represent a relationship between concepts in the causal map. The matrix representation of a causal map is shown in Figure 3. Figure 4 shows the adjacency matrix for the causal map in Figure 1.

The individual matrices are then added to combine the individual causal maps. Figure 3 shows how 5 concepts and 4 links in the causal map of prospective buyer 1 are added to 5 concepts and 4 links in the causal map of prospective buyer 2. The union of the two causal maps results in the aggregated causal map consisting of 7 concepts and 6 links. Programs such as Netanalysis [Narayanan, 1995] can be used to aggregate the individual causal maps. An individual file is created for each expert that contains all the cause-effect links (including direction and sign) identified by the expert. The program then aggregates the individual files of each expert by representing the causal map of each expert in the form of an adjacency matrix and then adding these adjacency matrices. It then provides the output in the form of an aggregated adjacency matrix.

VALIDATION OF STRUCTURE OF AGGREGATED CAUSAL MAP

The purpose of validating the aggregated causal map is to confirm the expert knowledge represented in the causal maps and to remove biases in the form of misrepresented links in the map. The focus on textual analysis can sometimes create biases in the process of deriving causal maps [Nadkarni and Shenoy, 2001; Rossi et al., 1983]. These biases may result in misrepresentation of the presence/absence of a link between two concepts, directionality of the link, and direct/indirect links in the map.

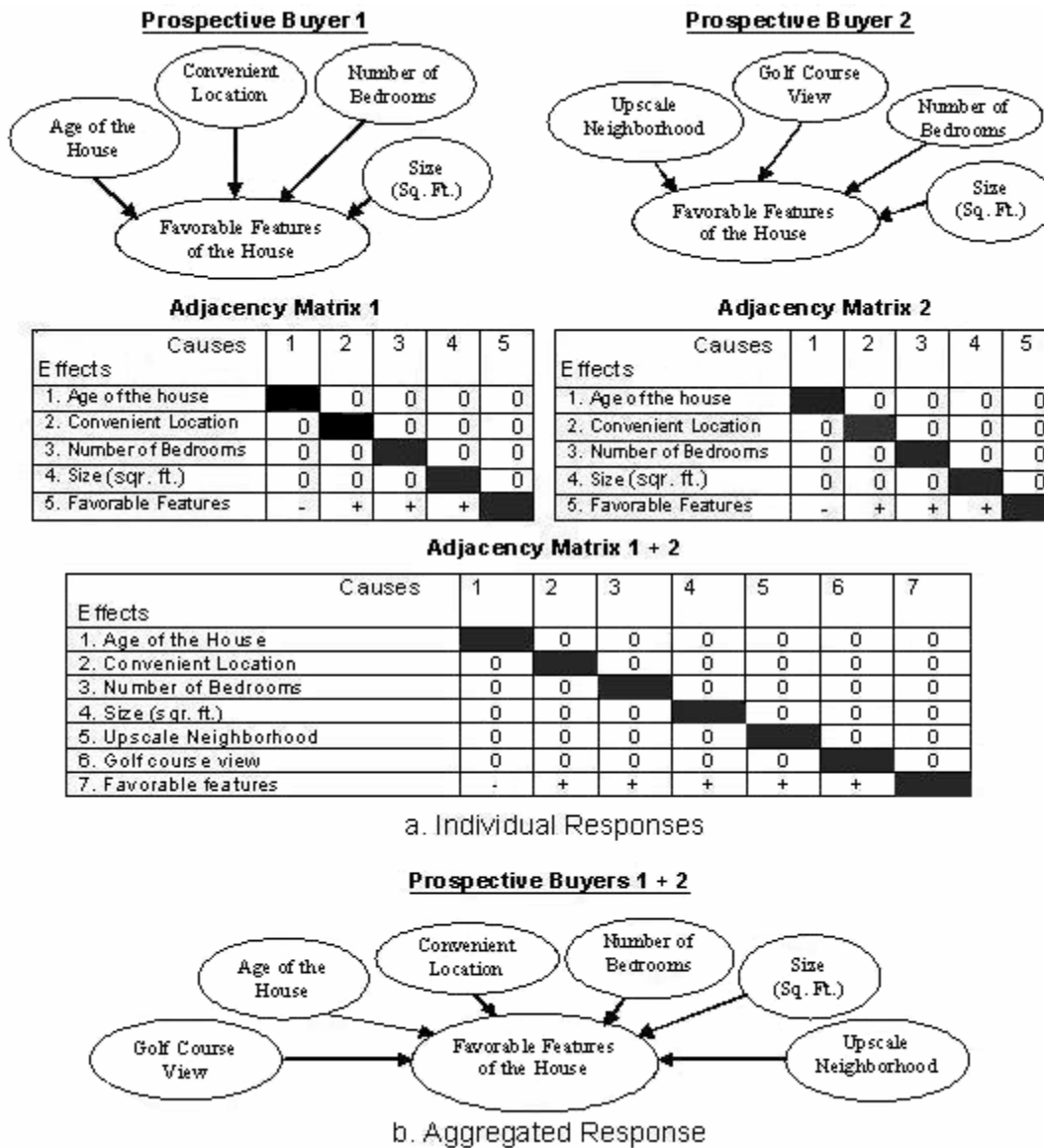


Figure 3. Procedure for Aggregating Individual Causal Maps

Effects	Causes	1	2	3	4	5	6	7	8	9	10
1. Mortgage Rate		■	0	0	0	0	0	0	0	0	0
2. % Down Payment		0	■	0	0	0	0	0	0	0	0
3. Favorable Financing		-	-	■	0	0	0	0	0	0	0
4. Convenient Location		0	0	0	■	0	0	0	0	0	0
5. Age of the House		0	0	0	0	■	0	0	0	0	0
6. Number of Bedrooms		0	0	0	0	0	■	0	0	0	0
7. Size		0	0	0	0	0	0	■	0	0	0
8. Price		0	0	0	+	-	+	+	■	0	0
9. Favorable Home Features		0	0	0	+	-	+	+	0	■	0
10. Buy the House		0	0	+	0	0	0	0	-	+	■

Figure 4. The Adjacency Matrix for Causal Map Shown in Figure 1

Three examples of the biases are:

1. Absence of a link between two concepts in a causal map may not mean that the concepts are independent. Concepts that are separated in the map may actually be related, but the expert may not explicitly state the link in his/her interview response.

2. The wording of the expert may lead to a reverse direction of the relationship between concepts in the causal map. A link from cause to effect may be represented as effect to cause.

3. A link between two concepts in the causal map implies that the relationship may either be direct or indirect. It is important to ensure that all the direct and indirect links between concepts are represented accurately in the causal map.

Nomothetic methods are the most appropriate tools to remove these biases.

Structured methods are appropriate tools to eliminate these three biases that result in misrepresentations in the maps, and to validate the knowledge represented in the map. The two most widely used structured methods are:

- structured interviews and
- adjacency matrices.

In structured interviews, the experts are provided a list of paired concepts and different alternative specifications about the relationships between the concepts. The experts are then instructed to choose an alternative to specify the direct relationship between the pair of concepts. Figure 5 illustrates a part of a structured interview filled by a prospective home buyer.

Alternatively, experts can be provided the concepts in the form of an adjacency matrix (as shown in Figures 3 and 4), where the rows represent effects and columns represent causes. The experts are asked to enter '0' (no relation), '+' (positive relation) or '-' (negative relation) in each cell to specify the relationship between two concepts in the matrix. These structured methods help in removing biases relating to the absence of links, misrepresentation of the directionality, and the lack of distinction between direct and indirect relationships.

Illustration of a Structured Interview

Directions: Please circle one of the four alternatives provided to specify the type of direct relation between the concepts listed below. Also circle the sign associated with the relation.

1. Price of the house	a) --	b) <input checked="" type="radio"/> \rightarrow	c) \leftarrow	d) \leftrightarrow	Decision to buy the house
		+ or <input checked="" type="radio"/> -			
2. Size (in s qr. ft.)	a) --	b) <input checked="" type="radio"/> \rightarrow	c) \leftarrow	d) \leftrightarrow	Decision to buy the house
		<input checked="" type="radio"/> + or -			
3. Size (in s qr. ft.)	a) --	b) <input checked="" type="radio"/> \rightarrow	c) \leftarrow	d) \leftrightarrow	Price of the house
		<input checked="" type="radio"/> + or -			
4. Mortgage Rate	a) --	b) <input checked="" type="radio"/> \rightarrow	c) \leftarrow	d) \leftrightarrow	Favorable financing
		+ or <input checked="" type="radio"/> -			

Figure 5. Illustration of a Structured Interview

Disagreements Among Experts

One of the key aspects in the validation phase is the resolution of disagreements between individual experts. Disagreements between experts can occur over the presence or absence of a concept or a link between concepts, and the differences in the direction and sign of the links in

the aggregated causal map. To capture the experts' knowledge fully, the differences between the experts need to be included in the causal map. For example, the ACM should include all the concepts and directed links identified by the experts. However, some disagreements may occur. The Delphi method [Dalkey and Helmer, 1963; Dalkey, 1969; Linstone and Turoff, 1975] can be used to resolve disagreements.

The Delphi method involves collating and summarizing the individual responses relating to the disagreements and then circulating the results back to the participants in the form of a questionnaire, with anonymity as to the name of the respondent. In the questionnaire, the participants are given the opportunity to revise their previous responses and are asked to explain 'why' and 'how' they arrive at the revised responses. These questionnaires are then collected and analyzed. If an agreement is not achieved, the process will be repeated – where the individual experts' responses and explanations are consolidated, summarized, and distributed to all participants in the next round. The rounds continue until a consensus is reached. In the process of resolving the disagreements using the Delphi method, new concepts or links may be proposed which further clarify and enrich the ACM. In the rare situations where a consensus cannot be reached (i.e., disensus), a majority rule may be used [Rantilla and Budescu, 1999].

DERIVATION OF CAUSAL VALUES OF AGGREGATED CAUSAL MAP

In this step, the individual causal values are elicited and disagreements between experts are resolved using the Delphi method. The individual values are then aggregated using probabilistic coding techniques. This step, therefore, involves the following three parts:

- Derivation of individual causal values
- Resolving disagreements among experts
- Aggregation of individual causal values

Derivation of Individual Causal Values

A variety of direct and indirect encoding techniques are available to elicit the causal values of individual experts associated with each link in the aggregated causal map. The direct methods are better suited for eliciting expert knowledge than indirect network-based tools for two reasons.

1. Direct methods elicit the causal values by asking the subjects to assign a strength value to the link. On the other hand, in the network-based methods, causal values are derived from frequencies of the mention of the link in the narrative [Carley and Palmquist, 1992]. These frequencies capture the strength indirectly and are affected by a number of biases including the length of the interview, content of the interview, and interviewer bias.
2. Unlike the frequencies, the direct techniques capture the uncertainties associated with the links more comprehensively [Forrester, 1961]. These uncertainties are especially important in decision-making.

Many different direct encoding techniques are available in which a subject responds to a set of questions directly by providing numbers [Spetzler and von Holstein, 1975]. The choice of the method depends on the preferences of the subject. (For a detailed review see [Spetzler and von Holstein, 1975]). The three most widely used encoding methods for eliciting causal values directly are: cumulative probability, fraction, and verbal encoding.

- In the cumulative probability method, the subject is asked to assign the cumulative probability associated with the link. This probability value can be expressed as an absolute number (0.40) or as a number on a discrete scale ("four on a scale of zero to ten"). The rating is then converted to a scale of 0 to 1.
- In the fraction method, the probability is expressed in the form of a fraction ("three-fourths: 3/4" or "four-tenths: 4/10").

- Verbal coding uses verbal descriptions to characterize events in the first phase of the encoding procedure. The descriptors used are those to which the subject is accustomed, such as “high,” “medium,” or “low.” The quantitative interpretation of the descriptors is then encoded in a second phase.

The form chosen to express the causal value (absolute number, percentage, fraction or verbal) should be the one most familiar to the subject. In causal maps representing broad and highly differentiated knowledge domains that consist of many specialized sub-domains, not all experts may be in a position to provide causal values for each link. In these cases, the causal values of multiple experts from each of the sub-domains should be elicited to represent the causal values of the links comprehensively and accurately in the causal maps.

Resolving Disagreements Among Experts

Once the causal values are elicited, the next step is to eliminate the biases and noise that occur in the elicitation of causal values. The Delphi technique is useful in verifying differences and minimizing noise in the causal value elicitation process that may result from experts assigning polar causal values to the same link. We note, however, that the primary purpose of the Delphi method is not to force convergence among the different experts, but to verify and confirm the initial weights provided by the experts. The Delphi method eliminates direct social contact that may bias or further polarize the outcomes, provides summarized and collated feedback to all participants, and allows participants to revise their individual opinions based on the feedback [Lock, 1987]. Hence, the experts may revise their causal values based on the consolidated feedback from the other experts. This process may be repeated for several rounds, until a satisfactory level of agreement (threshold) is reached, or, in a structured and non-fuzzy domain, until the level of saturation is reached whereby experts do not make any additional changes to the causal values.

The Delphi approach can capitalize on group process gains and expert disagreements to both enrich and validate the ACM while minimizing process losses and biases. The following are important features of the Delphi method [Awad, 1996]:

- *Anonymous response* – it removes or minimizes the chances of one expert influencing or biasing another expert's responses.
- *Controlled feedback* – it allows each expert to rethink any previous responses in light of the anonymous feedback and explanations from other experts.
- *Statistical group response* – the final opinion of the experts is an aggregation of the experts' individual responses in the final round.

In summary, a series of questionnaires may be administered using the Delphi approach to pool the experts' responses concerning their area(s) of disagreements. In each round, the individual experts' responses are shared with the other experts to facilitate their reaching an acceptable level of agreement on the weights of the links. The experts may respond to each disagreement by elaborating on the concepts or links or by revising the causal values on which the disagreements arise. These elaborations help in removing elicitation biases, verifying the causal values assigned by the experts, and reducing the gap between polar causal values assigned by different experts.

Aggregation of Individual Causal Values

The next step is to aggregate the causal values of individual experts. Many techniques are available in the decision-making and artificial intelligence literatures [Clemen, 1989; Alexander and Evans, 1988; Turban, 1992; Medsker et al., 1995] to aggregate the individual probabilities and weights assigned by the individual experts to the links. These approaches include:

- *Consensus methods* – aim to achieve agreement among experts with diverse knowledge.
- *Specific lines of reasoning* – multiple, distinct lines of reasoning are captured in such a way that a specific line of reasoning is selected based on the situation.

- *Blackboard systems* – the problem domain is decomposed into specialized knowledge sources to maximize independence among knowledge sources and to recognize the specializations of different experts.
- *Analytical approaches* – structured numerical methods that are most appropriate when expertise can be expressed in numeric values.

Each of these approaches is discussed next.

The consensus methods, which include the nominal-group technique (NGT), Delphi, and consensus decision-making, are the most appropriate for reaching agreement among a group of experts [Awad, 1996; McGraw and Seale, 1988; McGraw and Harbison-Briggs, 1989]. Dalkey and Helmer [1963] are the pioneers in using the Delphi method to derive consensus opinion of a group of experts whereas Hamilton and Breslawski [1996] used the Delphi-based approach to integrate the knowledge of multiple, geographically dispersed experts. Medsker et al. [1995] and Liou [1992] described the use of other consensus methods to aggregate the knowledge of multiple experts.

Specific lines of reasoning approaches involve keeping multiple experts' lines of reasoning distinct and then, based on the characteristics of each situation, selecting a specific line of reasoning that is most appropriate for the situation [Scott et al., 1991]. According to the procedure, "multiple lines of reasoning are allowed to coexist without unwanted interactions which could compromise an expert's advice" [Alexander and Evans, 1988, p.50]. In other words, based on information specific to a decision situation, a specific line of reasoning will be selected to produce the most appropriate solution [LaSalle and Medsker, 1991].

Blackboard systems approaches are most appropriate when all participants are experts who acquired their own expertise in situations different from those of the other experts in the group [Awad, 1996]. They are based on the concept of independent cooperating experts who constantly monitor and contribute knowledge to the blackboard. The blackboard systems are most useful for structuring complex problem-solving tasks that require multiple experts in different sub-areas of the domain [Corkill, 1991; Nii, 1986].

Analytical approaches are structured methods of aggregating knowledge of multiple experts. Such aggregation approaches include Bayesian networks [Morris, 1974, 1977, 1983], classical models (e.g., simple/weighted average [Clemen, 1989; Makridakis and Winkler, 1983; O'Leary, 1993], discriminant analysis [Mak et al., 1996; Blin and Whinston, 1975], maximum entropy [Myung et al., 1996]), and neural networks [Mak et al., 1996; Wang, 1996]. Mak et al. (1996) found that neural networks outperformed classical statistical methods (logit regression and discriminant analysis), the ID3 pattern classification method and the k-NN (Nearest Neighbor) technique in robustness and predictive accuracy, whereas a robust conclusion of the forecasting literature indicates that the simple and/or weighted average methods produce near perfect accuracy and work better than complex normative methods [Rantilla and Budescu, 1999]. The simple average method is appropriate when the experts are equally qualified in the various sub-areas of the domain whereas the weighted average method can be used to model differences in their degrees of expertise across specialized sub-domains.

A Combined Approach to Aggregate Individual Causal Values

In this study, we combine three of the four aggregation approaches mentioned above to develop a comprehensive and robust technique of aggregating individual causal values by capitalizing on the strengths of each approach. We used

1. the *simple average* method when all experts offered similar levels of expertise in the various sub-domains and the *weighted average* method when the levels of expertise across the sub-domains differed across the experts.
2. the Delphi technique from the *consensus* methods to resolve conflicts among individual experts.

3. the *blackboard* approaches in conjunction with the weighted average method to partition the problem domain into its sub-domains and to assign the relative weights for each expert in the respective subdomains.

The approach we adopted is only one of the many combinations of approaches that can be used. A comprehensive comparison of the different aggregation methods is beyond the scope of this paper.

IV. ILLUSTRATION

DOMAIN

This section provides an illustration of the ACM method to aggregate knowledge of multiple experts involved in the adoption of an Enterprise Resource Planning (ERP) system at ABC University. ERP is an enterprise-wide packaged solution that integrates the data and information of various departments and functions across an organization into a single system. The ERP adoption decision at the institution prior to Y2K was complex and varied. It involved not only diverse departments and functions, but also different levels of people. A variety of factors played an important role in this adoption including

- restructuring of the organizational processes and work systems to adopt ERP successfully,
- reducing user anxiety in using the ERP,
- the Y2K compliance problem, and
- budgeting the cost of adopting and implementing ERP.

Moreover, since the ERP adoption decision considerations in a non-profit institution context may differ from those in for-profit corporate organizations in which most ERP packages were sold, the complex and unique decision context is especially appropriate for the construction of an ACM. We illustrate our ACM procedure by capturing expert knowledge about the factors that were critical to ERP adoption in a public institution context and show how the various factors identified by experts influence each other and the ERP adoption.

CHOICE OF EXPERTS

Our sampling strategy was guided by two key criteria: (1) relevance of the experts sampled and (2) adequacy of the sample. The first step was to identify key decision makers who were most closely involved in the ERP adoption decision. We determined the key decision makers from a series of data sources including interviews with the Chief Information Officer (CIO) and Associate Chief Information Officer (ACIO) at the institution as well as official documents on ERP adoption and implementation reports, formal organizational charts, and goal charter plans. These sources yielded the key decision makers shown in Figure 6.

Expert Relevance

The Vice President of Business and Finance (VP-B&F) was the Chief Financial Officer of the institution and played an important role in budgeting and approving the ERP adoption decision. The CIO was in charge of all the administrative information systems at the institution. He developed the ERP planning strategy, and formed various functional and technical teams to manage the technical and organizational facets of ERP planning. He also presented and communicated the ERP adoption plans and presented decision briefings to top management. The ACIO was the "Technical and Data Conversion Leader" in the ERP implementation. His role involved developing and customizing components of the ERP system that were required to fit business needs. He also played a crucial role in the feasibility studies conducted to determine whether to adopt ERP at the institution. The Director of Administrative Systems was the primary liaison between the technical experts and the users. He was in charge of analyzing the business processes and organizational infrastructure, and the financial function issues in the ERP adoption

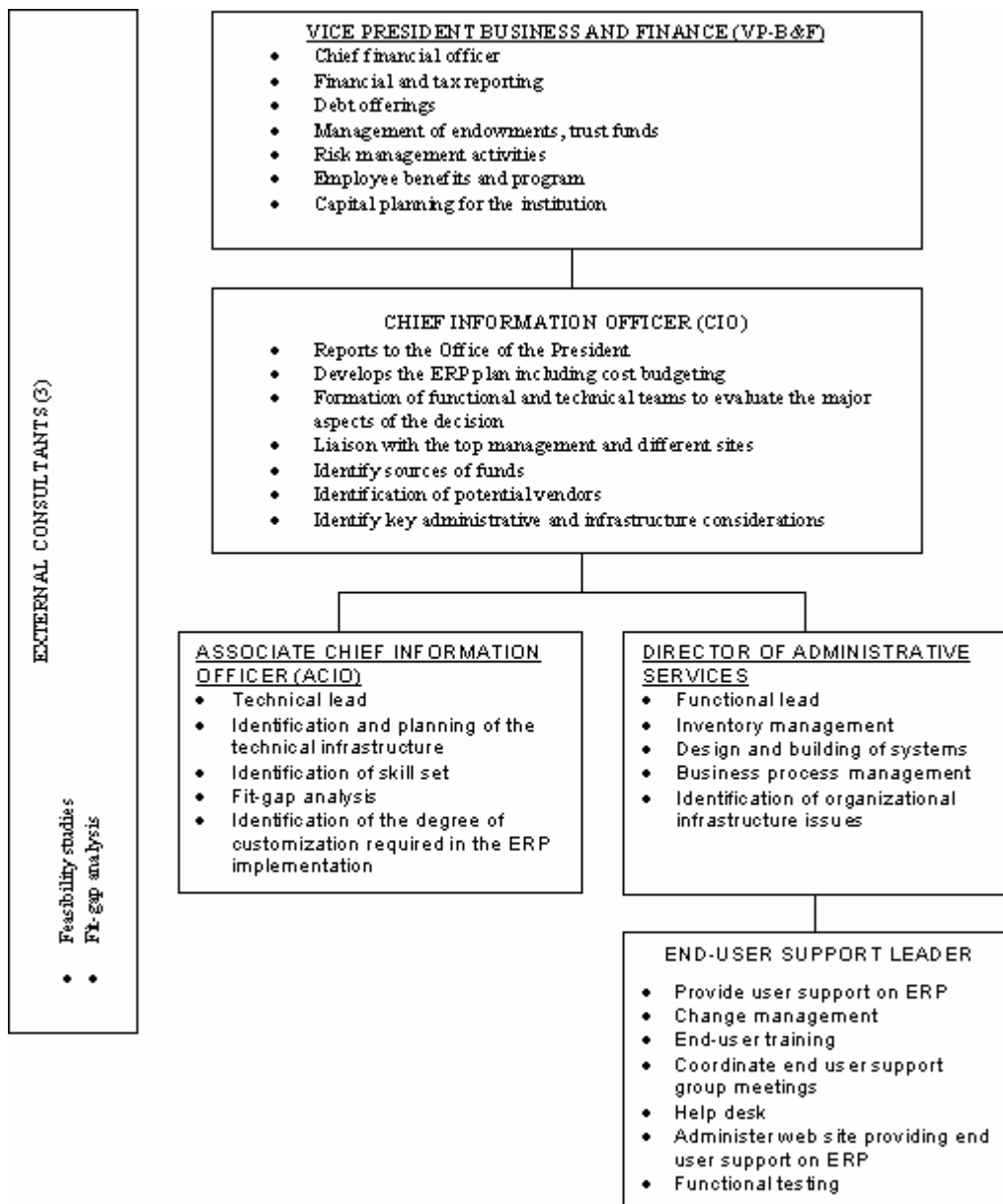


Figure 6. Key Decision Makers in the ERP Adoption Decision at the Institution

decision. The End-user Support Team Leader provided necessary change management efforts in the area of end-user support, training, and education, and the system tests for the functional users. He provided feedback on user needs and change management issues in the ERP adoption decision.

In addition to the key internal decision makers of the ERP adoption decision, we also interviewed three senior consultants from two consulting companies that conducted feasibility and fit-gap analysis of the potential ERP systems for the institution. Because of the turnover of consultants, we could not find the consultants who conducted feasibility studies. Thus, we selected three senior consultants from the same two consultancy firms that were familiar with ERP projects and were involved in similar projects in other public institutions. The three consultants were selected

based on their resumes and recommendations of their peers. The consultants were surrogates who represented an outsider view of the ERP adoption decision. Hence, a total of eight experts were interviewed to acquire their causal map on the domain of ERP adoption decisions.

Sample Adequacy

The second key issue in sampling is the adequacy of the sample. The basic question is, “Is our sample adequate to comprehensively represent the ERP adoption decision?”

The number of experts required to represent a specific domain comprehensively is contingent on a variety of factors, including the nature of the domain and the diversity and depth of expert knowledge. Selection of a large number of experts may yield large and comprehensive causal maps, but at the same time can be prohibitively costly in terms of time and money. On the other hand, selection of a few experts may be convenient and fast, but may not adequately capture the casual variables of a domain. The notion of point of redundancy or saturation is useful in determining the optimal number of experts required to capture the domain variables exhaustively without using an excessively large number of experts [Axelrod, 1976; Nelson et al., 2000; Yin, 1994]. The point of redundancy is calculated by starting sequentially with the causal map of the first expert and then adding one additional individual at a time to find the additional concepts identified by each additional expert. The additional concepts and links yielded by adding the revealed causal map of each individual respondent are measured by plotting a curve as shown in Figure 7. When additional subjects do not yield new concepts or links between concepts, then the point of redundancy is reached and inclusion of additional experts will not make any additional contribution to the ACM. Figure 7 shows that the point of redundancy was reached for our sample after the fourth expert (41 concepts in the map), suggesting that the first four interviews exhausted the ERP adoption decision variables. Experts 5, 6, 7 and 8 did not contribute additional concepts or links between concepts to the ACM. The curve in Figure 7 was sequenced according to the order of interviews with experts—Associate CIO, End-user Support Leader, CIO, Director of Administrative Services, VP Business and Finance, followed by the three consultants.

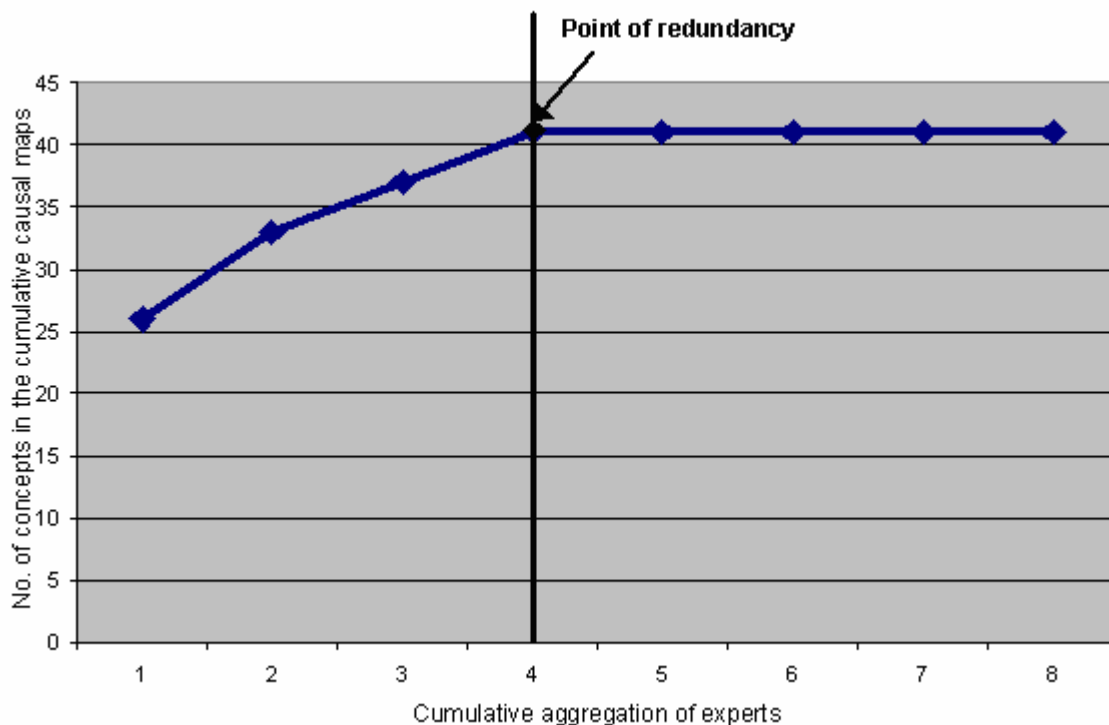


Figure 7. Point of Redundancy

PROCEDURES IN CONSTRUCTING THE ACM

Step 1: Data Elicitation

The experts were interviewed individually in sequence using an open-ended interview with probes. Each interview lasted about two hours. The interview began with a broad question: "What do you think were the key factors affecting ERP adoption in a public institution environment?" The subsequent 'probes' were based on the factors suggested by the expert. The probing continued until a comprehensive list of ERP adoption factors was elicited and the subjects could not think of any additional factors. Follow-up interviews were conducted with each expert to clarify and elaborate issues discussed in the initial interviews.

Step 2: Derivation of Individual Causal Maps

Individual causal maps of the experts were constructed from the narratives yielded by the interviews using a four-step procedure shown in Figure 2.

1. *Identifying causal statements.* Two raters including a researcher in ERP collectively identified the causal statements based on a comprehensive list of causal connectors developed by the same two raters.
2. *Raw causal maps.* The causal statements identified in step 1 were manually broken into causal phrases, causal connectors, and effect phrases to derive the raw causal maps.
3. *Coding scheme.* The two raters coded the phrases in the raw causal maps into generalized concepts and consulted with the experts to ensure that the coded concepts did not deviate from the original cause and effect phrases used by the experts in their interview responses.
4. *Coded causal map.* Using the coding scheme developed in the previous step, the raw causal maps were converted into coded maps. The Netanalysis program was used to construct the causal maps of individual experts. Each input file (for each individual expert) contained all the *causal pairs* identified by the expert in the form of causal concept, effect concept, direction of the link, and sign of the link. The program then identifies the common concepts between different causal pairs and links these causal pairs. It provides the output in the form of an adjacency matrix that includes all the links between the pairs of concepts in the map.

Step 3: Aggregation of Individual Causal Maps

As discussed before, the individual causal maps were first represented as adjacency matrices. The columns in an adjacency matrix are causes and rows are effects. A '+' (positive relation), '-' (negative relation) or '0' (no relation) (see Figure 3) was entered in the respective cell of the adjacency matrix to represent a relation between every two concepts in the matrix. These individual matrices were then added to obtain the aggregated matrix for the combined causal map.

Step 4: Validation of Structure of ACM

The ACM was validated using the structured questionnaire. The original experts were each provided with a list of paired concepts and alternative specifications of the direction ($\rightarrow/\leftarrow/\leftrightarrow/0$) and sign (+: positive relation, -: negative relation, 0: no relation) of the relation between the concepts. The experts were then instructed to choose the alternative that best specified the relation between the pair of concepts. This validation procedure eliminated some coding biases by providing a check on:

- presence or absence of a link in the map,
- direction of the link in the map,
- coding of the phrases in the map,
- sign associated with the link (+ or -).

Figure 8 shows the post-validation ACM of the eight experts. If experts' opinions differed on the presence or absence of a link between two concepts, the link was included in the ACM to capture all possible links comprehensively. For example, in Figure 8, the link between 'vendor support' and 'cost of ERP consulting' was introduced after the validation step because some experts indicated a link (of negative relationship) between them during validation. In cases where an expert indicated both direct and indirect relations between two concepts, the expert was consulted to verify the relations between them – to determine if both the direct and indirect relations were valid or if the relations were indeed fully mediated. In our example (Figure 8), we verified that both the direct and indirect (i.e., via 'cost of ERP consulting' and 'cost of implementing ERP') links between 'vendor support' and 'ERP adoption decision' were valid. On the other hand, during the validation step, one expert specified both a direct relation between 'lack of data flexibility' and 'preference for upgrading existing legacy systems (vs. adopting ERP)'

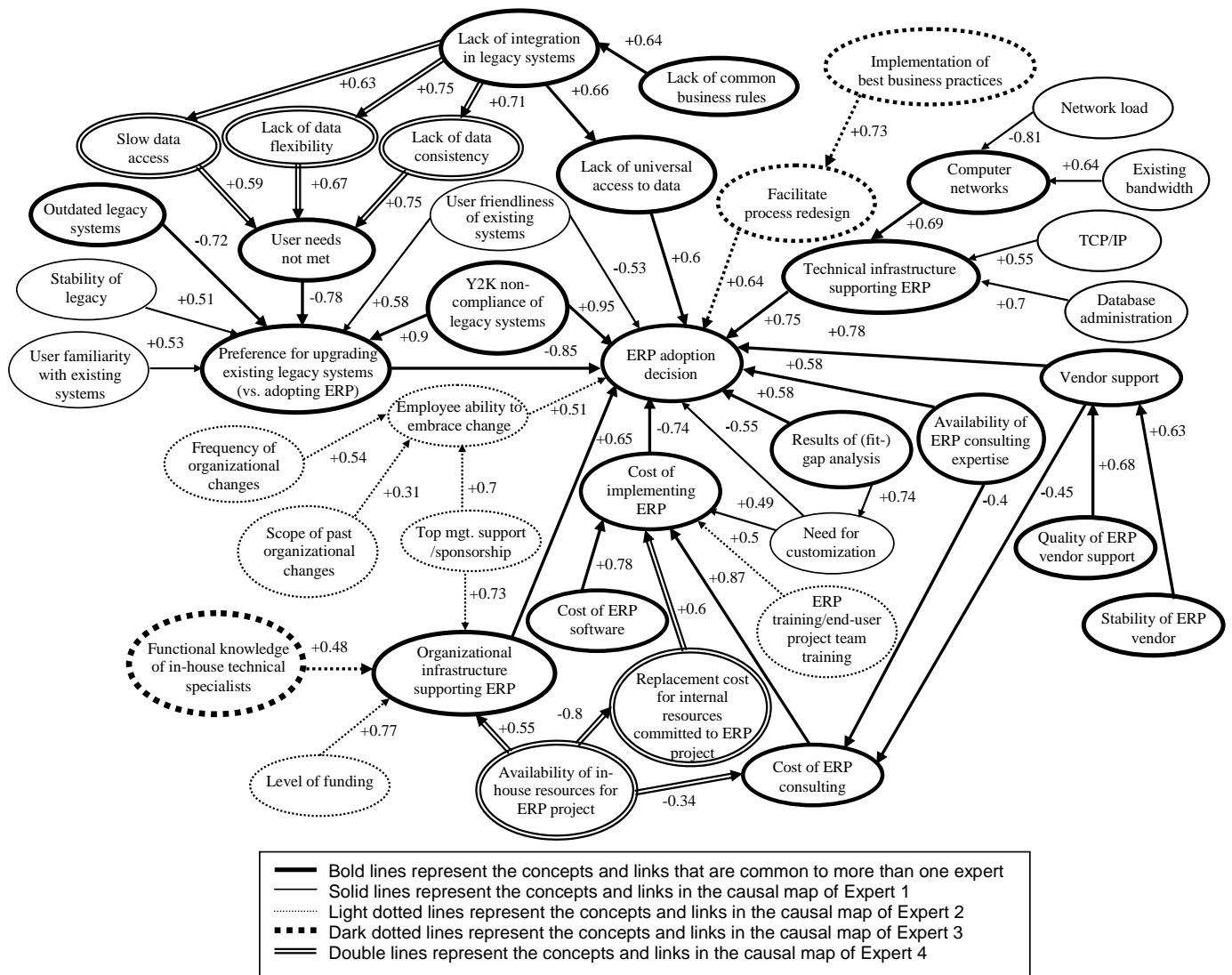


Figure 8. Aggregated Causal Map of the Experts

and an indirect relation between them via 'user needs not met.' We verified the relations with the expert and found that the relation was an indirect one, that is, it was fully mediated by 'user needs not met'. Any discrepancies in the presence or absence of links between the ACM obtained in the previous step and the outcome of the validation step were resolved by consulting with individual experts. When disagreements arose, all possible links were represented. Although we encountered some disagreements between experts in the presence or absence of links between concepts, no directions or signs (+/-) to the links conflicted.

As shown in Figure 8, the ACM of the eight experts yielded 41 concepts that affect the ERP adoption decision in the public institution environment. Of the 41 concepts in the ACM, 19 concepts were identified by more than one expert. The number of additional variables identified is shown in Table 2.

Table 2. Additional Variables

Expert	No. of Additional Variables	Main Type of Additions
Expert 1	8	Technical and systems considerations
Expert 2	6	End-user support, and organizational and people aspects of ERP adoption
Expert 3	3	Key motivations and considerations in ERP adoption.
Expert 4	5	Functional area and the users' perspectives

The diversity in the backgrounds, roles, and responsibilities of these experts resulted in capturing both commonly shared variables relating to the ERP adoption domain and unique variables in their areas of expertise and job responsibility.

Step 5: Derivation of Causal Values of ACM

The causal values of the ACM were derived by first eliciting causal values for each causal link individually from the experts and then aggregating the individual causal values provided by the experts using the appropriate aggregation rule. In deriving the individual causal values, the eight experts were given the choice of assigning the values using any one of the three encoding methods discussed earlier (cumulative probability, fractions, or verbal encoding). All of them chose to use the discrete scale of cumulative probability (e.g., "eight on a scale of zero to ten"). Next, the individual causal values of the experts were aggregated. Since the experts differed in their expertise relating to the different aspects of the ERP adoption decision, the weighted average method was more appropriate for aggregating the individual causal values. Aggregation was done in three steps.

Step 1. The Delphi method was carried out to resolve polar causal values where the difference in ratings assigned by the experts exceeded the pre-set threshold (i.e., specified on a rating scale of zero to ten). This 'discrepancy' threshold was arbitrarily pre-determined at 5 by the researcher (or knowledge engineer). In other words, a discrepancy occurred when the difference between the lowest and highest ratings given to a link was greater than the threshold of 5. The Delphi process was used to resolve the discrepancies and an agreement (i.e., discrepancies ≤ 5) was reached after the first round. In this case, a threshold of 5 represents an acceptable level of agreement given the diversity of the ERP domain and the differences in the knowledge and background of the experts. In general, the desired level of discrepancy threshold might vary depending on the domain and differences in the specialization of the experts.

Step 2. To identify the expertise of individual experts, the ERP decision domain was divided into multiple sub-domains. Three criteria were employed to enhance the robustness and validity of the classification scheme: (1) face validity, (2) theoretical meaningfulness, and (3) inter-rater reliability (Bagozzi, 1980). To address face validity of the classification scheme, we consulted four third party experts from the institution who not only were ERP researchers, but also followed the ERP implementation in the institution closely and interacted regularly with the original experts

regarding their roles and responsibilities in ERP implementation. They came closest to understanding both the issues in ERP adoption decisions in the institution and the different roles, responsibilities, and expertise of the original experts. These four third party experts examined the ACM, and identified four sub-domains relating to the ERP adoption decision domain –

- technological
- user support
- organizational
- implementation

To confirm the theoretical meaningfulness of the classification scheme, we reviewed prior ERP adoption literature to check the relevance and appropriateness of these domains and to identify other possible sub-domains. Theoretical meaningfulness is especially important to enhance the robustness and validity of the classification scheme (Bagozzi, 1980). The ‘technological’ and ‘organizational’ dimensions are identified as two key factors in information systems adoption (Premkumar et al., 1997; Iacovou, et al., 1995; Chwelos et al., 2001). ‘User support’ is particularly relevant and important in any ERP adoption decision and implementation (Shanks et al., 2000; Nah et al., 2001) since it plays a key role in explaining success or failure of an ERP implementation (Bingi et al., 1999; Nah et al., 2003). The ‘implementation’ dimension covers factors that relate specifically to the ERP implementation.

We validated the classification scheme by asking the four third party experts to independently carry out a Q-sort procedure (Anderson and Gerbing, 1991) to assess their inter-rater reliability. The procedure involved classifying or sorting each of the causal concepts in the ACM (except the final ‘ERP adoption decision’ concept) into one of the four categories or sub-domains. The degree of complete agreement across all four experts was high (88%), suggesting very good inter-rater reliability of the classification. The disagreements were discussed and resolved based on consensus, and the final classification that was agreed to by all of them is shown in Table3.

Table 3. Classification of the Causal Concepts in the ACM into ERP Adoption Sub-domains

Technological	Organizational	User support	Implementation
<ul style="list-style-type: none"> • Computer networks • DB administration • Existing bandwidth • Lack of data consistency • Lack of data flexibility • Lack of integration in legacy systems • Lack of universal access to data • Network load • Outdated legacy systems • Slow data access • Stability of legacy systems • TCP/IP • Technical infrastructure supporting ERP • User friendliness of existing systems • Y2K compliance of legacy systems 	<ul style="list-style-type: none"> • Availability of in-house resources for ERP project • Employee ability to embrace change • Frequency of organizational changes • Functional knowledge of in-house technical specialists • Lack of common business rules • Level of funding • Organizational infrastructure supporting ERP • Preference for upgrading existing legacy systems • Scope of past organizational changes • Top management support/sponsorship 	<ul style="list-style-type: none"> • User needs not met • User familiarity with existing systems • ERP training/end-user project team training 	<ul style="list-style-type: none"> • Availability of ERP consulting expertise • Cost of ERP consulting • Cost of ERP software • Cost of implementing ERP • Facilitate process redesign • Implementation of best business practices • Need for customization • Quality of ERP vendor support • Replacement cost for internal resources committed to ERP project • Results of fit-gap analysis • Stability of ERP vendor • Vendor support

Step 3. To obtain the weights for each of the sub-domains, two approaches are suggested [Ayyub, 2000]. The first approach involves asking each individual expert to rate their knowledge and experience of each sub-domain (e.g. on a 0-10 point scale) and then computing the relative level of expertise (i.e., relative weights) of each expert on each sub-domain. The second approach uses third party experts such as seniors or peers to rate the individual experts after which an average rating of each expert could be computed to arrive at a robust indicator of each expert's level of expertise. In our study, we used the third party approach to enhance the objectivity and inter-rater reliability of the ratings.

Two of the third party experts who interacted regularly with the experts in the study independently rated the experts (on a scale of 0 to 1) on their level of knowledge and experience on each of the four sub-domains identified. The eight experts (including the outside consultants) were rated based on their educational qualifications, job title and responsibilities, prior work experience, and (except for the outside consultants) their role in the ERP adoption decision. The third party experts rated the three consultants based on their qualifications, ERP experience, and their roles on comparable ERP projects. Table 4 shows both of their ratings (separated by a backslash '/') as well as the average of their ratings (in parentheses).

Table 4. Two Third Party Ratings of the Sub-Domain Knowledge and Experience of Each Expert

	Technological	Organizational	User support	Implementation
Expert-1	0.8 / 0.9 (0.85)	0.5 / 0.6 (0.55)	0.3 / 0.3 (0.3)	0.8 / 0.6 (0.7)
Expert-2	0.6 / 0.4 (0.5)	0.7 / 0.5 (0.6)	1.0 / 0.8 (0.9)	0.7 / 0.5 (0.6)
Expert-3	0.4 / 0.6 (0.5)	0.9 / 0.6 (0.75)	0.3 / 0.2 (0.25)	0.6 / 0.5 (0.55)
Expert-4	0.5 / 0.4 (0.45)	0.6 / 0.4 (0.5)	0.8 / 0.8 (0.8)	0.7 / 0.6 (0.65)
Expert-5	0.4 / 0.2 (0.3)	0.8 / 0.8 (0.8)	0.5 / 0.4 (0.45)	0.8 / 0.7 (0.75)
Expert-6 ⁺	0.4 / 0.3 (0.35)	0.5 / 0.3 (0.4)	0.8 / 0.7 (0.75)	0.8 / 0.6 (0.7)
Expert-7 ⁺	0.9 / 0.8 (0.85)	0.2 / 0.2 (0.2)	0.1 / 0.2 (0.15)	0.5 / 0.4 (0.45)
Expert-8 ⁺	0.2 / 0.1 (0.15)	0.7 / 0.7 (0.7)	0.2 / 0.1 (0.15)	0.4 / 0.6 (0.5)

* First third-party rating / second third-party rating (average rating)

⁺ Experts 6, 7 and 8 are surrogate consultants

The inter-rater reliability of the two raters was computed based on the degree of agreement in their ratings. The overall inter-rater reliability can be expressed as:

$$1 - \frac{\sum_{i=1}^I \sum_{j=1}^J |X_{ij} - Y_{ij}|}{I * J}$$

where X_{ij} is the first third party expert's rating on Expert- i in sub-domain j

Y_{ij} is the second third party expert's rating on Expert- i in sub-domain j

I is the number of original experts (in this case, it is 8)

J is the number of sub-domains identified (in this case, it is 4)

As illustrated in Table 5, the numerator in the second part of the above formula is $1.1+1.0+0.7+1.2 = 4.0$ while the denominator is $4 \times 8 = 32$. Hence, the overall inter-rater reliability is $(1 - (4/32)) = 87.5\%$. Table 5 also computes the inter-reliability for each of the sub-domains, which is 86% for technological, 88% for organizational, 91% for user support, and 85% for

implementation. Since the inter-rater reliability for each of the four sub-domains is at least 80%, the ratings of the two third party experts were consistent and reliable.

Table 5. Computation of Inter-Rater Reliability of the Two Third Party Ratings

	Technological	Organizational	User support	Implementation
Expert-1	$ (0.8 - 0.9) = 0.1$	$ (0.5 - 0.6) = 0.1$	$ (0.3 - 0.3) = 0$	$ (0.8 - 0.6) = 0.2$
Expert-2	$ (0.6 - 0.4) = 0.2$	$ (0.7 - 0.5) = 0.2$	$ (1.0 - 0.8) = 0.2$	$ (0.7 - 0.5) = 0.2$
Expert-3	$ (0.4 - 0.6) = 0.2$	$ (0.9 - 0.6) = 0.3$	$ (0.3 - 0.2) = 0.1$	$ (0.6 - 0.5) = 0.1$
Expert-4	$ (0.5 - 0.4) = 0.1$	$ (0.6 - 0.4) = 0.2$	$ (0.8 - 0.8) = 0$	$ (0.7 - 0.6) = 0.1$
Expert-5	$ (0.4 - 0.2) = 0.2$	$ (0.8 - 0.8) = 0$	$ (0.5 - 0.4) = 0.1$	$ (0.8 - 0.7) = 0.1$
Expert-6	$ (0.4 - 0.3) = 0.1$	$ (0.5 - 0.3) = 0.2$	$ (0.8 - 0.7) = 0.1$	$ (0.8 - 0.6) = 0.2$
Expert-7	$ (0.9 - 0.8) = 0.1$	$ (0.2 - 0.2) = 0$	$ (0.1 - 0.2) = 0.1$	$ (0.5 - 0.4) = 0.1$
Expert-8	$ (0.2 - 0.1) = 0.1$	$ (0.7 - 0.7) = 0$	$ (0.2 - 0.1) = 0.1$	$ (0.4 - 0.6) = 0.2$
Sub-total	1.1	1.0	0.7	1.2
Inter-rater reliability	$1 - (1.1/8.0) = 86\%$	$1 - (1.0/8.0) = 88\%$	$1 - (0.7/8.0) = 91\%$	$1 - (1.2/8.0) = 85\%$

Table 6 shows the normalized average ratings¹ on each sub-domain. These normalized ratings were used as the relative weights for determining the final causal value of link belonging to that sub-domain. For example, if a causal link connected two technological concepts, then expert-1 was assigned a weight of 0.215, expert-2 and expert-3 were each assigned a weight of 0.127, expert-4 was assigned a weight of 0.114, expert-5 was assigned a weight of 0.076, etc. For causal links connecting concepts from different domains, we used a simple average of the normalized weights of each of the experts across the domains. Fourteen of the 52 causal links in the ACM connect concepts from different domains. For example, the six causal links connecting technological and organizational concepts (e.g., the causal link from 'outdated legacy systems' to 'preference for upgrading existing legacy systems') were assigned a weight of 0.1685 $[(0.215+0.122)/2]$ for expert-1, 0.13 $[(0.127+0.133)/2]$ for expert-2, 0.147 $[(0.127+0.167)/2]$ for expert-3, etc. Figure 8 shows the final causal values of the ACM.

Table 6. Total, Average, and Normalized Third Party Ratings of Each Expert in Each Sub-Domain

	Technological	Organizational	User support	Implementation
Expert-1	$0.85 / 3.95 = 0.215$	$0.55 / 4.5 = 0.122$	$0.3 / 3.75 = 0.080$	$0.7 / 4.9 = 0.143$
Expert-2	$0.5 / 3.95 = 0.127$	$0.6 / 4.5 = 0.133$	$0.9 / 3.75 = 0.240$	$0.6 / 4.9 = 0.122$
Expert-3	$0.5 / 3.95 = 0.127$	$0.75 / 4.5 = 0.167$	$0.25 / 3.75 = 0.067$	$0.55 / 4.9 = 0.112$
Expert-4	$0.45 / 3.95 = 0.114$	$0.5 / 4.5 = 0.111$	$0.8 / 3.75 = 0.213$	$0.65 / 4.9 = 0.133$
Expert-5	$0.3 / 3.95 = 0.076$	$0.8 / 4.5 = 0.178$	$0.45 / 3.75 = 0.120$	$0.75 / 4.9 = 0.153$
Expert-6	$0.35 / 3.95 = 0.089$	$0.4 / 4.5 = 0.089$	$0.75 / 3.75 = 0.200$	$0.7 / 4.9 = 0.143$
Expert-7	$0.85 / 3.95 = 0.215$	$0.2 / 4.5 = 0.044$	$0.15 / 3.75 = 0.040$	$0.45 / 4.9 = 0.092$
Expert-8	$0.15 / 3.95 = 0.038$	$0.7 / 4.5 = 0.156$	$0.15 / 3.75 = 0.040$	$0.5 / 4.9 = 0.102$
Total avg. rating	3.95	4.5	3.75	4.9

* Average rating (from Table 4) / total average rating = normalized rating

¹ Normalized average rating of each expert on a sub-domain = (average rating of each expert by third party raters on the sub-domain / total average third party ratings for all experts on the sub-domain)

As presented in Figure 8, Y2K compliance was one of the key factors leading to ERP implementation at the institution. Other important factors included technical and organizational infrastructure supporting ERP, cost of implementing ERP, degree of vendor support, and the lack of universal access to data. Each of these factors was in turn caused or influenced by other sub-factors. For example, one of the main reasons for the lack of universal data access was due to the lack of integration in the existing legacy systems. Although the ACM in this illustrative example was constructed from eliciting the knowledge of multiple experts involved in ERP implementation at a public institution, a more generalized (meta-) ACM can be constructed by aggregating multiple ACMs from different ERP contexts using the same ACM procedure.

V. CONCLUSIONS

The ACM method outlined in this paper contributes in many ways to existing research on eliciting knowledge from multiple experts.

1. It uses a new approach, the causal mapping approach, to elicit, aggregate, and represent knowledge of multiple experts.

2. The idiographic approach used in constructing the causal map allows knowledge engineers to capture the knowledge of experts about complex and emerging domains where hard data is difficult to obtain and boundaries of the domain are not clearly defined.

3. This method is able to capitalize on the advantages of eliciting knowledge from a group of experts without relying on group interaction to pool the knowledge of diverse experts. Hence, it minimizes group process biases associated with group decision-making.

4. The biases that may arise because of the use of an idiographic method can be successfully eliminated using a nomothetic approach. Hence the ACM method integrates the idiographic and nomothetic methods of constructing causal maps. In doing so, it combines the advantages of the two approaches while reducing both of their limitations.

The ACM method is versatile and lends itself to a variety of quantitative analyses. The aggregation and discrepancy resolution procedures outlined in this paper could be modified and used in quantitative analyses based on Bayesian networks, neural networks and decision trees, and other analyses.

Semi-automated software such as CODEMAP [Carley and Palmquist, 1992], Netanalysis [Narayanan, 1995], UCI Net [2002] and Decision Explorer [2003] are useful in constructing aggregated causal maps. Recent research has focused on automating the causal mapping process fully. Process automation should further simplify the implementation of our ACM method in different domains.

This study is just a first step towards proposing the use of a causal mapping procedure in eliciting knowledge from multiple experts. We welcome any future research efforts that are directed towards designing tools to translate the rules presented in this paper into workable decision tools to facilitate the aggregation process.

The limitations of our approach also deserve acknowledgement.

1. The approach is time consuming and tedious, and requires significant commitment of time and effort on the part of both the experts and knowledge engineers. Thus, the method may not be appropriate for relatively simple and standard domains, where nomothetic methods may be more pragmatic and efficient than the ACM approach. However, the time and effort spent in the knowledge elicitation technique proposed in the current study will generate significant added value in the case of complex and ill structured domains.

2. Although the Delphi technique is known to resolve conflicts successfully across experts in most cases, the Delphi technique occasionally results in disensus among experts. In such cases, the alternative is to use the majority rule, in which the views of the majority are imposed on the views of the minority. This approach may result in force-fitting bias in conflict resolution.

In summary, we propose a user-friendly, intuitive, and reliable approach to aggregate the knowledge of multiple experts. We show that the proposed ACM procedure is not only suitable for capturing the various factors, sub-factors and their inter-relationships in a domain area, but it can also aggregate the different factors and relationships elicited from multiple experts. In future research, we are interested in comparing the ACM procedure with other methods of aggregating

expert knowledge, and extending the ACM procedure to take into account the variety of quantitative analyses that can be used with it.

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REFERENCES

- Alexander, S.M. and G.W. Evans (1988) "The Integration of Multiple Experts: A Review of Methodologies" in E. Turban and P. Watkins (eds.), *Applied Expert Systems*, New York, NY: North-Holland, pp. 47-53.
- Anderson, J.C. and D.W. Gerbing (1991) "Predicting the Performance of Measures in a Confirmatory Factor Analysis with a Pretest Assessment of their Substantive Validities," *Journal of Applied Psychology*, 76(5), pp. 732-740.
- Awad, E.M. (1996) *Building Expert Systems: Principles, Procedures and Applications*, New York, NY: West Publishing.
- Axelrod, R. (1976) *The Structure of Decision*, Princeton, NJ: Princeton University Press.
- Ayyub, B.M. (2000) *Methods for Expert-Opinion Elicitation of Probabilities and Consequences for Corps Facilities*, Alexandria, VA: Institute for Water Resources, Report 00-R-10, available at: <http://www.iwr.usace.army.mil/iwr/pdf/MethodsforEEfinal1.PDF>.
- Bagozzi, R.P. (1980) *Causal Models in Marketing*, New York, NY: Wiley.
- Bingi, P., M.K. Sharma and J. Godla (1999) "Critical Issues affecting an ERP Implementation," *Information Systems Management*, 16(2), pp. 7-14.
- Blin, J.M. and A.B. Whinston (1975) "Discriminant Functions and Majority Voting," *Management Science*, 21(5), pp. 1439-1440.
- Brown, S.M. (1992) "Cognitive Mapping and Repertory Grids for Qualitative Survey Research: Some Comparative Observations," *Journal of Management Studies*, 29(3), pp. 287-305.
- Carley, K. and M. Palmquist (1992) "Extracting, Representing and Analyzing Mental Models," *Social Forces*, 70, pp. 601-636.
- Chwelos, P., I. Benbasat and A.S. Dexter (2001) "Research Report: Empirical Test of an EDI Adoption Model," *Information Systems Research*, 12(3), pp. 304-321.
- Clemen, R.T. (1989) "Combining Forecasts: A Review and Annotated Bibliography," *International Journal of Forecasting*, 5, pp. 559-583.
- Corkill, D.D. (1991) "Blackboard Systems," *AI Expert*, 6(9), pp. 40-47.
- Dalkey, N.C. (1969) *The Delphi Method: An Experimental Study of Group Opinion*, Santa Monica, CA: RAND Corporation.
- Dalkey, N.C. and O. Helmes (1963) "An Experimental Application of the Delphi Method to the Use of Experts," *Management Science*, 19(3), pp. 458-467.
- Decision Explorer (2003) www.banxia.com, Glasgow, UK: Banxia Software Ltd.
- Deing, R., A. Giboin, P.A. Tourtier and O. Corby (1992) "Knowledge Acquisition for Explainable, Multi-Expert Knowledge-Based Design Systems," *Proceedings of European Workshop on Knowledge Acquisition, Modeling and Management: Current Developments in Knowledge*, Berlin/Heidelberg, pp. 298-317.
- Eden, C., F. Ackermann and S. Cropper (1992) "The Analysis of Cause Maps," *Journal of Management Studies*, 29(3), pp. 309-323.
- Eden, C. and Ackermann, F. (1998) "Analyzing and Comparing Idiographic Causal Maps" in C. Eden and J.C. Spenders (eds.) *Managerial and Organizational Cognition: Theory, Methods and Research*, London, UK: Sage.
- Forrester, J.W. (1961) *Industrial Dynamics*, Cambridge, MA: MIT Press.
- Hamilton, D.M. and S. Breslawski (1996) "Knowledge Acquisition for Multiple Site, Related Domain Expert Systems: Delphi Process and Application," *Expert Systems with Applications*, 11(3), pp. 377-389.
- Hodgkinson, G.P., N.J. Brown, A.J. Maule, K.W. Glaister and A.D. Pearman (1999) "Breaking the Frame: An Analysis of Strategic Cognition and Decision Making Under Uncertainty," *Strategic Management Journal*, 20, pp. 977-985.
- Huff, A.S. (1990) *Mapping Strategic Thought*, Chichester, UK: Wiley.

- Iacovou, C.L., I. Benbasat and A.S. Dexter (1995) "Electronic Data Interchange and Small Organizations: Adoption and Impact of Technology," *MIS Quarterly*, 19(4), pp. 465-486.
- LaSalle, A.J. and L.R. Medsker (1991) "Computerized Conferencing for Knowledge Acquisition from Multiple Experts," *Expert Systems with Applications*, 3, pp. 517-522.
- Linstone, H.A. and M. Turoff (1975) *The Delphi Method*, Reading, MA: Addison-Wesley. (Available in electronic form: <http://www.is.njit.edu/pubs/delphibook/>).
- Liou, Y.I. (1992) "Collaborative Knowledge Acquisition," *Expert Systems with Applications*, 5, pp. 1-13.
- Lock, A. (1987) "Integrating Group Judgments in Subjective Forecasts" in G. Wright and P. Anyton (eds.), *Judgmental Forecasting*, New York, NY: Wiley.
- Maines, L.A. (1996) "An Experimental Examination of Subjective Forecast Combination," *International Journal of Forecasting*, 12, pp. 223-233.
- Mak, B., T. Bui and R. Blanning (1996) "Aggregating and Updating Experts' Knowledge: An Experimental Evaluation of Five Classification Techniques," *Expert Systems with Applications*, 10(2), pp. 233-241.
- Makridakis, S. and R.L. Winkler (1983) "Average of Forecasts: Some Empirical Results", *Management Science*, 29(9), pp. 987-996.
- Massey, A. and W.A. Wallace (1991) "Focus Groups as a Knowledge Elicitation Technique: An Exploratory Study," *IEEE Transactions on Knowledge and Data Engineering*, 3(2), pp. 193-200.
- McDermott, J. (1981) "R1: The Formative Years," *AI Magazine*, 2(6), pp. 21-29.
- McGraw, K.L. and B.K. Harbison-Briggs (1989) *Knowledge Acquisition: Principles and Guidelines*, Englewood Cliffs, N.J.: Prentice Hall.
- McGraw, K.L. and M.R. Seale (1988), "Knowledge Elicitation with Multiple Experts: Considerations and Techniques," *Artificial Intelligence Review*, 2, pp. 31-44.
- Medsker, L., M. Tan, and E. Turban (1995) "Knowledge Acquisition from Multiple Experts: Problems and Issues," *Expert Systems with Applications*, 9(1), pp. 35-40.
- Mittal, S. and C.L. Dym (1985) "Knowledge Acquisition from Multiple Experts," *AI Magazine*, 6(2), pp. 32-36.
- Moore, C.J. and J.C. Miles (1991) "Knowledge Acquisition Using More than one Expert to Cover the Same Domain," *Artificial Intelligence Review*, 5, pp. 255-271.
- Morris, P.A. (1974) "Decision Analysis Expert Use," *Management Science*, 20(9), pp. 1233-1241.
- Morris, P.A. (1977) "Combining Expert Judgments: A Bayesian Approach," *Management Science*, 23(7), pp. 679-693.
- Morris, P.A. (1983) "An Axiomatic Approach to Expert Resolution," *Management Science*, 29(1), pp. 24-32.
- Myung, I.J., S. Ramamoorti and A.D. Bailey (1996) "Maximum Entropy Aggregation of Expert Predictions," *Management Science*, 42(10), pp. 1420-1436.
- Nadkarni, S and P. Shenoy (2001) "A Bayesian Network Approach to Making Inferences in Causal Maps," *European Journal of Operations Research*, 128(3), pp. 21-40.
- Nah, F., S. Faja and T. Cata (2001) "Characteristics of ERP Software Maintenance: A Multiple Case Study," *Journal of Software Maintenance and Evolution*, 13(6), pp. 399-414.
- Nah, F., J. Mao and I. Benbasat (1999) "The Effectiveness of Expert Support Technology for Decision Making: Individuals versus Small Groups," *Journal of Information Technology*, 14(2), pp. 137-147.
- Nah, F., K.M. Zuckweiler and J.L. Lau (2003) "ERP Implementation: Chief Information Officers' Perceptions of Critical Success Factors," *International Journal of Human Computer Interaction*, 16(1), pp. 5-22.
- Narayanan, V.K. (1995) "Netanalysis," University of Kansas, School of Business, Lawrence, Kansas.
- Nelson, K, S. Nadkarni, V.K. Narayanan, and M. Ghods (2000) "Understanding Software Maintainer Expertise: A Causal Mapping Approach," *MIS Quarterly*, 24(3), pp. 475-507.
- Nii, P.H. (1986) "Blackboard Application Systems, Blackboard Systems and a Knowledge Engineering Perspective," *AI Magazine*, 7(3), pp. 82-106.
- Nunamaker, J.F., A.R. Dennis, J.S. Valacich, D.R. Vogel, J.F. George (1991), "Electronic Meeting Systems to Support Group Work," *Communications of the ACM*, 34(7), pp. 40-61.

- O'Leary, D.E. (1993) "Determining Differences in Expert Judgment: Implications for Knowledge Acquisition and Validation," *Decision Sciences*, 24(2), pp. 395-407.
- O'Leary, D.E. (1998) "Knowledge Acquisition from Multiple Experts: An Empirical Study," *Management Science*, 44(8), pp. 1049-1058.
- Premkumar, G., K. Ramamurthy and M. Crum (1997) "Determinants of EDI Adoption in the Transportation Industry," *European Journal of Information Systems*, 6(2), pp. 107-127.
- Rantilla, A.K. and D.V. Budescu (1999) "Aggregation of Expert Opinion," *Proceedings of the 32nd Hawaii International Conference on System Sciences*.
- Rossi, P.H., J.D. Wright and A.B. Anderson (1983) "Handbook of Research Methods", Orlando, FL: Academic Press Inc.
- Rush, R. and W.A. Wallace (1997) "Elicitation of Knowledge From Multiple Experts Using Network Inference," *IEEE Transactions on Knowledge and Data Engineering*, 9(5), pp. 688-696.
- Scott, A.C., J.E. Clayton and E.L. Gibson (1991) *A Practical Guide to Knowledge Acquisition*, Reading, M.A.: Addison-Wesley.
- Shanks, G., A. Parr, B. Hu, B. Corbitt, T. Thanasankit and P. Seddon, P. (2000) "Differences in Critical Success Factors in ERP Systems Implementation in Australia and China: A Cultural Analysis," *Proceedings of the 8th European Conference on Information Systems*, Vienna, Austria, 537-544.
- Shaw, M.E. (1971) *Group Dynamics: The Psychology of Small Group Behavior*, McGraw Hill.
- Smith, R.G. and J.D. Baker (1983) "The Dipmeter Advisor System--A Case Study in Commercial Expert System Development," *Proceedings of the Eighth International Joint Conference on Artificial Intelligence*, pp. 122-129.
- Spetzler, C.S. and C.S.S. von Holstein (1975) "Probability Encoding in Decision Analysis," *Management Science*, 22(3), pp. 340-358.
- Steier, D.M., R.L. Lewis, J.F. Lehman and A.L. Zachen (1993) "Combining Multiple Knowledge Sources in an Integrated Intelligent System," *IEEE Expert*, 8(3), pp. 35-43.
- Steiner, I.D. (1972) *Group Process and Productivity*, New York, NY: Academic Press.
- Tan, F.B. and M.G. Hunter (2002) "The Repertory Grid Technique: A Method for the Study of Cognition in Information Systems," *MIS Quarterly*, 26(1), pp. 39-57.
- Turban, E. (1992) *Expert Systems and Applied Artificial Intelligence*, New York, NY: Macmillan Publishing.
- Turban, E. and M. Tan (1993) "Methods for Knowledge Acquisition From Multiple Experts—An Assessment," *International Journal of Applied Expert Systems*, 1(2), pp. 101-119.
- Turban, E. and J.E. Aronson (1998) *Decision Support Systems and Intelligent Systems*, Fifth Edition, Upper Saddle River, NJ: Prentice Hall.
- UCInet 5 (2002) www.analytictech.com, Harvard, MA: Analytic Technologies Inc.
- Wallsten, T.S., D.V. Budescu, I. Erev and A. Diedrich (1997a) "Evaluating and Combining Subjective Probability Estimates," *Journal of Behavioral Decision Making*, 10, pp. 243-268.
- Wallsten, T.S., D.V. Budescu and C.J. Tsao (1997b) "Combining Linguistic Probabilities," in *Psychologische Beiträge*, 39(1-2), pp. 27-55.
- Wang, S. (1996) "A Dynamic Perspective of Differences between Cognitive Maps," *Journal of the Operational Research Society*, 47, pp. 538-549.
- Yaniv, I. (1997) "Weighting and Trimming: Heuristics for Aggregating Judgments under Uncertainty," *Organizational Behavior and Human Decision Processes*, 69, pp. 237-249.
- Yin R.K. (1994) *Case Study Research: Design and Methods*, Second Edition. Thousand Oaks, CA: Sage.

GLOSSARY OF TERMS

Adjacency matrix	A matrix representation of a causal map in which columns are causes and rows are effects.
Causal concept	A single ideational category in the form of an attribute, issue, factor or variable of a domain that is represented by a node in the causal map.
Causal connection	A tie that links two concepts in a map and is presented with a unidirectional arrow.
Causal map	A directed graph characterized by a hierarchical structure which is most often in the form of a means/end graph.
Causal value	A representation of the strength of the causal connection.
Delphi method	A multi-round method involving collating and summarizing the individual participants' responses and then, after each round, circulating the results in the form of questionnaire to all participants.
Direct encoding techniques	Methods that directly elicit causal values by asking the subjects to assign a strength value to each link.
Filtering	The process of determining which part of the text to code, and what words to use in the coding scheme.
Idiographic approach	An exploratory approach that inductively explores new knowledge relating to a specific domain using qualitative and unstructured methods.
Narrative	The text representing experts' responses to unstructured interviews that is used to construct causal maps.
Nomothetic approach	A confirmatory approach that tests widely accepted and generalized assumptions relating to a specific domain using structured methods.

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