# Knowledge dependencies in Fuzzy Information Systems Evaluation

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## ABSTRACT

Experience and research within the field of Information Systems Evaluation (ISE), has traditionally centered on providing tools and techniques for investment justification and appraisal, based upon explicit knowledge which encodes financial and other direct situational factors (such as accounting, costing and risk metrics). However, such approaches tend not to include additional causal interdependencies that are based upon tacit knowledge and are inherent within such a decision-making task. The authors show the results of applying a cognitive mapping approach, in the guise of a Fuzzy Cognitive Mapping (FCM) simulation, i.e. Fuzzy Information Systems Evaluation (F-ISE), in order to highlight the usefulness of applying such a technique. The authors highlight those contingent and necessary knowledge dependencies, in an exploratory sense, which relate to the investment appraisal decision-making task, in terms of the interplay between tacit and explicit knowledge, in this regard.

## KEYWORDS

Fuzzy Cognitive Mapping, Information Systems Evaluation, Knowledge Management

## INTRODUCTION

In recent years the increasing importance of IT/IS in organizations has meant that the implementation of new technology is one of the most lengthy, expensive and complex tasks that a firm can undertake (Small and Chen, 1995). The level of investment required for such technology implies that issues involving project justification should assume great importance. However, in order for senior management to commit to any expenditure, they need to be convinced of the business justification of such investments (Butler, 1997; Farbey, Land and Target, 1993; Primrose, 1991; Willcocks, 1994). Appraisal techniques such as Return on Investment (RoI), Internal Rate of Return (IRR) and Net Present Value (NPV) are often used to assess capital investments (Willcocks 1994). These methodologies are based on conventional accountancy frameworks where project costs are set against quantifiable benefits to be achieved (Carlson, 1992; Hochstrasser, 1992; Primrose, 1991). Several researchers explain that any quest for a 'one size fits all' method of IS Evaluation (ISE), is fruitless because the range of circumstances to which any such technique can be applied, is so varied that no one technique can cope – especially when quantifying human and organizational benefits (Farbey *et al*., 1993; Maskell, 1991). Existing research suggests that many companies have no formal IT justification process, and furthermore, there is a lack of adequate post-implementation audit against which project objectives can be measured (Hochstrasser 1992; Remenyi, Money, Sherwood-Smith and Irani, 2000). As such, the extensive time and money invested in IT/IS is frequently not perceived to be delivering the business benefits that were initially intended (Irani, Ezingeard, Grieve and Race, 1999; Remenyi *et al*., 2000). Thus, the authors take the view that the decision-making processes inherent within ISE, includes implicit or tacit knowledge interrelationships that are not normally taken into consideration, in a *prima facie* sense. In the majority of manufacturing companies, a formal justification proposal must be prepared and accepted by decision-makers, prior to any expenditure. Furthermore, Typical ISE requires the involvement of key stakeholders impacted by the investment process: senior management, project managers, users and support staff (such as IT). Key shortcomings of this approach are that not all participants may have the necessary authority or experience to assist in this process (i.e. not all stakeholders may be experts).

Also, it may be difficult for management to understand the implications of choosing a particular ISE approach (Farbey *et al.*, 1993). In order to investigate this, the authors present the application of a Fuzzy Cognitive Mapping (FCM) to two given ISE scenarios within a manufacturing case study organization (hence defining a fuzzy ISE, F-ISE). By analyzing key knowledge dependencies required in this modeling approach, the authors provide insight into the application of such an Artificial Intelligence (AI) technique as a Decision Support System (DSS) tool, for assisting the ISE decision-making task.

## FUZZY COGNITIVE MAPPING (FCM): A BRIEF INTRODUCTION

Traditional approaches to modeling dynamic, systems such as those encountered in economic, social and political sciences have tended to rely upon the technique of cognitive mapping to elucidate system definitions and inter-relationships. In a similar manner, the technique of Fuzzy Cognitive Mapping (FCM), which is based upon the science of Fuzzy Logic (Zadeh, 1965), is a natural extension to cognitive maps developed in these disciplines (Axelrod, 1976; Mentezemi and Conrath, 1986). An FCM is a method to represent state variables within a dynamical system graphically, by links that signify cause and effect relationships, being augmented with fuzzy or multivalent weights, quantified via numbers, or words (Kosko, 1990; Mls, 2004). Visually, an FCM is essentially a non-hierarchic digraph from which changes to each statement, hence fuzzy concept (i.e. node), are governed by a series of causal increases or decreases in fuzzy weight values (i.e. links between nodes). The advantage of modelling dynamic systems such as those mentioned above via an FCM, is that even if the initial mapping of the problem concepts is incomplete or incorrect, further additions to the map can be included, and the effects of new parameters can be quickly seen (thus providing a holistic picture of the scenario being modeled). An example FCM of conditions that affect driving in bad weather (Kosko, 1990) is shown in Figure 1.

The positive (+) and negative (-) signs that connect each fuzzy concept denote causal relationships in terms of descriptors. The map is read by seeing which concept is linked together with another one, and uses the '+' or '-' signs above each arrowed line to provide a causal relationship between them. Such mappings have proved useful in analyzing systems which cannot normally be described via traditional flow-graph methods, as Aguilar (2005) highlights for application to: learning strategic rules for games; agricultural production systems; clinical diagnosis; eCommerce planning; and legal negotiation.

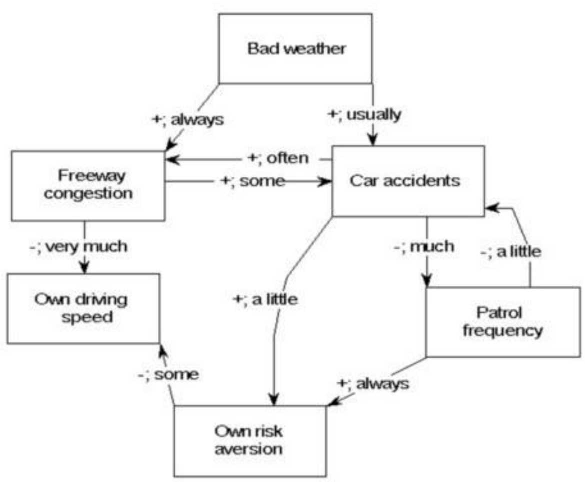



**Figure 1. An FCM of driving in wet weather (from Kosko, 1990)**

### Machine Learning in FCMs: causal simulation

FCMs are highly amenable for enumeration and can be run as simulations also, as the causal interrelationship mappings that are linked in this way, essentially define a directed graph or collection of linked nodes. Given an FCM with a number of nodes, $C_i$ where $i = 1\ldots n$ exists, the value of each node in an iteration, can be computed from the values of the nodes in the preceding state, using the following equation:

$$C_i^{t+1} = f\left(\sum_{j=1}^{n} W_{ij}\, C_i^{t}\right) + C_i^{t-1} \qquad (1)$$

where $C_i^{t+1}$ is the value of the node at the $t$ + 1 iteration, $C_i^{t-1}$ is the value of the node at the $t$ - 1 iteration, $f$ is a given threshold or transformation function, $W_{ij}$ is a corresponding fuzzy weight between two given nodes, $i$ and $j$, and $C_i^{t}$ the value of the interconnected fuzzy node at step $t$ (Cordoro and Palaez, 2002; Kosko, 1991; Stylios, Georgopoulos, and Groumpos, 1997). The threshold function, $f$ (x), can be constructed as being bivalent (x = 0 or 1); trivalent (x = -1, 0 or 1); hyperbolic (usually tanh (x)); or the sigmoidal / step function ($x = 1 / 1 + e^{-cx}$, where $c$ is a constant). In order to simulate the dynamic behavior of the FCM, therefore requires the additional definition of the fuzzy weights, $W_{ij}$, within a connection matrix, $W$, and the initial or starting input vector at time $t$, $C^t$. As such, the latter is a 1 x n row vector with the values of all concepts, $C_1$, $C_2,\ldots, C_n$ for $n$ concepts or nodes in the FCM, whilst the former is a $n$ x $n$ matrix of weights between any two fuzzy nodes, $w_{ij}$. If there is no direct relationship between the i$^{th}$ and j$^{th}$ nodes, then the value of the connection strength is zero. As such, the connection / influence matrix, $W$, can be written as:

$$W = \begin{bmatrix} \cdots & \cdots & \cdots \\ \cdots & w_{ij} & \cdots \\ \cdots & \cdots & \cdots \end{bmatrix} \qquad (2)$$

Whilst the initial row vector can be represented as:

$$C^0 = \left(w_{i,j}^{1},\ldots,w_{i+1,j+1}^{n}\right) \qquad (3)$$

for $n$ nodes in the FCM. The values within this vector signify the activation level of a node in the FCM. Hence each $w_{i,j}^{n}$ value defines an initial static state of the FCM, for which each node is set to an "on", "off" or other intermediary position. The simulation proceeds by computing $C_i^{t+1}$ based upon this initial starting vector, and the given threshold function in $f$, as well as the causal connection strengths in the $n$ x $n$ matrix, $W$. Each subsequent $t$ + 1 iteration then uses the values of the preceding $t$ – 1 row vector in $C^0$. By calculating each subsequent value of equation (1), the FCM simulates the dynamical system being modeled. Each corresponding linked node within the mapping responds to its respective inputs – the state of each, defining any underlying modality or "hidden pattern of inference". As such, the input influence matrix in equation (2) is essentially a set of training data, and thus the iterative application of equation (1) describes a machine learning process (similar to a supervised Neural Network, Simpson, 1990).

## RESEARCH METHODOLOGY AND CASE STUDY

To investigate and describe the core issues associated with the evaluation of IT/IS within a manufacturing setting, the research design and methodology is now presented. This encompasses the definition of appropriate research questions posed; the selection and design of an appropriate theoretical and methodological stance (an exploratory, empirical case study-based research); and use of an appropriate data collection and coding protocol (transcribed semi-structured interviews and company reports and literature). The primary step in defining this research was to investigate the utility of using such an AI technique for the particular case of evaluating an MRPII investment in a UK manufacturing company. This was in order to capture and outline those inherent organizational and individual factors involved in this decision-making task, to model those aspects that impinge upon given ISE processes (i.e. via an FCM). Furthermore, the application of this approach to ISE was exploratory, as there has been little or no published work on the subject (see for example, Aguilar, 2005). The overall research design itself, involved the identification of the latter need for a more 'intelligent' decision-making support tool (based upon a review of the extant literature); the selection of an appropriate case environment and participants exhibiting ISE issues (via purposive sampling); the selection of a methodological stance; the use of a research protocol to gather and categorize case data for presentation and analysis (by means of semi-structured interviews, observations and case company archive material); developing and analyzing results of specific FCMs of the ISE (generating FCM weight matrices and causal modifiers then deducing meaning from results via narrative description); and finally identifying lessons to be learned from the case analysis presented.

By applying such an approach, essentially a Fuzzy ISE (F-ISE), the authors felt it was possible to encapsulate the ISE approach taken within the case company, by evaluating multi-valued or fuzzy concepts. This was achieved through active participation between both the researchers and case participants within a workshop setting. This was done so that the researchers could better understand any nuances inherent in the formation of each causal node. The workshop participants were also asked to agree on words that could describe their perception or expectation of a particular part of ISE task (for example, "contributes to", "highly valued"). Once this data was collected by the authors, it was then coded and categorized into issue groupings (for example, strategic, tactical, operation, risk, benefits of costs). Following this, the researchers then arranged the causal weights, and influence matrix, $W$, and generated an initial FCM. This was then shown to the ISE experts within the case company, whereupon feedback from them, the influence matrix was revised as well as a set of ISE scenarios to be used for the FCM simulations. Upon this agreement, an appropriate threshold function, $f$ , was chosen and the simulations were run and results analyzed. To generate the results shown in the proceeding sections, the authors used a spreadsheet-based model employing matrix multiplication and graph drawing add-ins in Excel (Volpi, 2004). Finally, the analysis was then synthesized and put into the context of assessing the approach as a potentially useful 'intelligent' DSS tool.

To summarize the extent of this approach used, the authors present the "building blocks" model, as used by Hjertzen and Toll (1994) in Table 1. This tabulation, allows the researcher to specify the focus of the research design along dimensions of research scope, methodology, data collection and analysis. The research approach described in Table 1, was applied in the similar manner as previous successful research carried out by the authors (Irani, Sharif, Love and Kahraman, 2001b; Sharif and Irani, 1999). The findings are considered appropriate to provide others with a frame of reference (even though Company A was not systematically sampled). Although it is not possible to generalize the findings for a wider population, this paper seeks to add to the field of simulation / evaluation approaches which complement existing ISE techniques.

| ***Research Component*** | ***Detail*** | ***Literature Grounding*** |
|---|---|---|
| **Scope** | ISE within a manufacturing organization | Irani and Love (2001); Pouloudi and Serafeimidis, (1999); Remenyi et al. (2000); |
| **Theory** | Exploratory research | Walsham (1993) |
| **Methodology** | Interpretivist (Qualitative), Empirical Case Study | Hakim (1987); Yin (1994) |
| **Data Collection** | ▪ Background theory / literature survey;<br>▪ Purposive sampling (selection of case participants);<br>▪ Primary sources: participant observation (overt observation, time bound and predetermined); semi-structured interviews with senior management and project implementation team (filter questions, with "probes" / verbalization)<br>▪ Secondary sources: company reports | Fielder (1987); Shaughnessy and Zeichmester (1994); |
| **Data Analysis** | Application of FCM technique and narrative description, in order to elucidate key aspects of ISE within the case organization | Denzin (1984); Kosko (1990) |

**Table 1. Research methodology components**

### Case Detail

The case organization used for the research, Company A, is a British manufacturing organization specializing in the discrete manufacture of aerospace, automotive, and other engineering components (Irani *et al*., 1999). The development and growth of this company has largely been due to previous successful technology investment in recent years. It's approach to evaluating and assessing investments in projects was deemed to be suitable for modeling using an FCM: as although it incorporated a typical financial accounting approach, it attempted to include human as well as capital costs and benefits. The decision-making scenario that was investigated, involved the evaluation of an integrated Manufacturing Resource Planning (MRPII) system (Irani, Sharif and Love, 2001a). At the time of investigation, this investment would enable Company A to maintain competitive advantage through the innovative use of this integrated manufacturing system. Within Company A, management viewed project justification as a hurdle that had to be overcome, and not as a technique for evaluating the project's worth. This had significant implications, as during the preparation of the MRPII project's proposal, managers spent much time and effort investigating its technical and financial aspects (in a strategic sense), rather than risk and benefit aspects (in a tactical / operational sense). Hence, the managing director of the firm became committed to the belief that the project was essential. As a result, the remaining project team members tried to address implementation and human resource risks, against estimated cost implications. So whilst there was a desire to invest and implement in technology, there were, in a sense, opposing causal views of the justification process. The resulting ISE case scenarios discussed also reflected a number of long-term (strategic, financially motivated) as well as short/medium-term foci (project costs, benefits, risks and value). As a result, a series of candidate scenarios for FCM simulation were chosen and are now described in the next section.

## FCM RESULTS

Against this backdrop, the authors now present the generation of two FCMs, relating to these factors, thereby attempting to highlight their use as a decision-making tool. Figure 2 and Figure 3 respectively detail FCMs that show a managerial view of the case study company's ISE approach (Irani *et al*., 2001b).

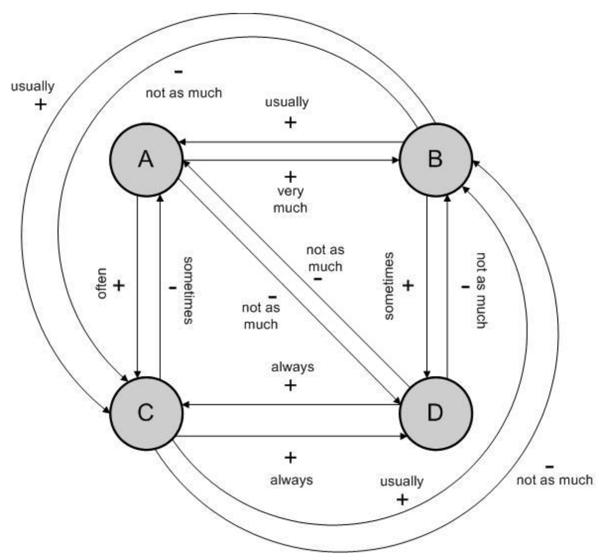



Figure 2. STOF FCM

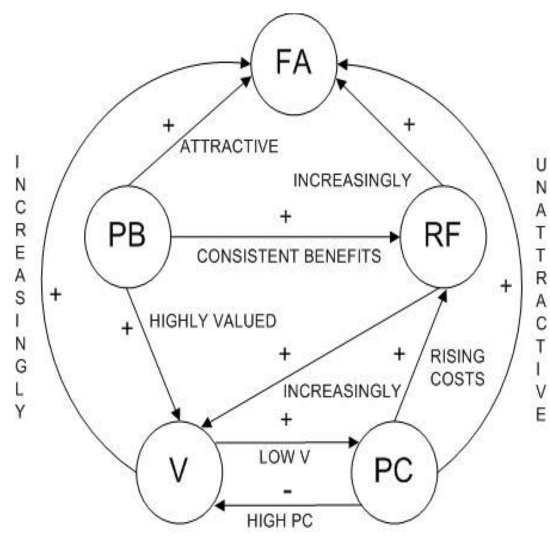



Figure 3. Functional Risks and Benefits FCM

This is in terms of using a Strategic, Tactical, Operational and Financial lens (Demmel and Askin, 1992) - henceforth known as the acronym, STOF; and a functional project risks, benefits and costs view based upon team member responses (Sharif and Irani, 1999). In Figure 1, A are Strategic Considerations; B are Tactical Considerations; C are Operational Considerations; D are Financial Considerations; + is a causal increase; and finally, - is a causal decrease. Likewise, in Figure 2 V denotes project value; PB are project benefits; PC are project costs; FA is financial appraisal; and RF are project risk factors. Using equations (1 – 3), we now present results of executing each FCM. The fuzzy connection matrices, are given in equation (4) and (5), and the causal modifiers are given in Table 1 and Table 2, for each FCM respectively.

$$W = \begin{bmatrix} 0.000 & 0.750 & 0.250 & 0.125 \\ 0.375 & 0.000 & 0.375 & 0.475 \\ 0.475 & 0.125 & 0.000 & 1.000 \\ 0.125 & 0.125 & 1.000 & 0.000 \end{bmatrix} \tag{4}$$

$$W = \begin{bmatrix} 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.750 & 0.000 & 0.250 & 1.000 & 0.000 \\ 0.500 & 0.000 & 0.000 & 0.500 & 0.000 \\ 0.500 & 0.000 & 0.000 & 0.000 & -0.250 \\ -1.000 & 0.000 & -0.250 & -0.500 & 0.000 \end{bmatrix} \tag{5}$$

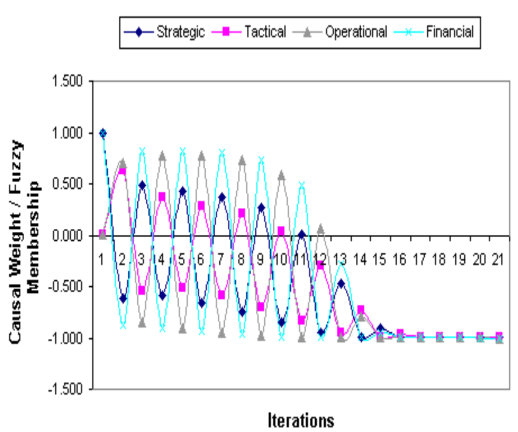
| ***Descriptor*** | ***Weight*** |
|---|---|
| Never | 0.000 |
| Not as much | 0.125 |
| Often | 0.250 |
| Usually | 0.375 |
| Sometimes | 0.475 |
| Very much | 0.750 |
| Always | 1.000 |

**Table 1. Causal weights for STOF FCM**

| ***Descriptor*** | ***Weight*** |
|---|---|
| Attractive | 0.75 |
| Increasingly | 0.50 |
| Consistent Benefits | 0.25 |
| Highly Valued | 1.00 |
| Low V | -0.25 |
| High PC | -0.50 |
| Rising Costs | -0.75 |
| Unattractive | -1.00 |

**Table 2. Causal weights for Functional FCM**

The threshold function, *f*, for advancing the FCM simulation as given in equation (1), was set to be the hyperbolic function, *f* (x) = tanh (x), for both FCMs. Likewise the starting row vector $C^0$ was set to [1 –1 –1 1] for the STOF FCM (i.e. a Strategic-driven view which assumes assuming Financial considerations are always inherently a part of any investment justification - known as Sim A); and [1 1 –1 1 1] for the functional FCM (i.e. where no risk factors for the investment justification are taken into account - known as Sim B). Figure 4 and 5 shows the resulting FCM output in each case.



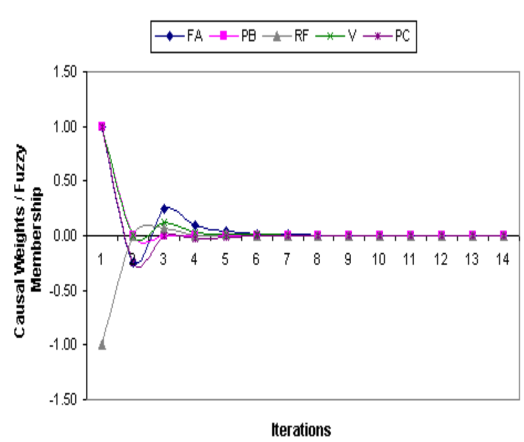



**Figure 4. Sim A result**

**Figure 5. Sim B result**

Figure 4 shows operational and financial considerations are almost double those of the Strategic and Tactical ones. This possibly highlights the dynamic of taking long-term costs and / or investments into account, until Strategic goals can be achieved. As such, it can be seen that overall, the influence of investment costs tend to reduce over time as Tactical and then Operational factors are brought into play. It is also interesting to note that the periodic response of this scenario is primary driven by the reducing effect of Tactical considerations, from iteration 4 onwards. Between iteration 11 and 12, when Strategic and Financial factors are very closely in phase and intersect one another, the cumulative effect of reducing Tactical considerations, suddenly has a strong dampening effect overall. In Figure 5, we also see that, within 8 iterations, no single concept dominates. Although known costs have an adverse effect on risks, these costs cannot be realized until a project's value emerges (in terms of realizable / evident benefits at iteration 2). In other words, once a project's value is defined, / realized project risks stabilize. As can be seen from the graph, risk factors RF, tend to stabilize and approach the fixed-point equilibrium first, followed by project benefits, PB; project value, V; project costs, PC; and finally financial appraisal techniques, FA. This furthermore denotes that in the absence of any associated project risks, investment evaluations which include at least benefit, value, and cost factors tend to dominate any financial motivations which may be involved or that may drive the initial justification (as shown from iteration 3 to iteration 6). In such a way, the authors believe that the application of an FCM approach provides further insight and stimulates discussion about the investment process and variables involved.

## KNOWLEDGE DEPENDENCIES

As can be seen from the generation and simulation of results of each FCM, this AI technique provides unique insights into the system dynamics of each of these models of ISE. However, in order to achieve this level of insight requires some knowledge of not only the fuzzy approach, but also the knowledge domain. At a fundamental level, an FCM therefore provides a mapping of *knowledge*, and is thus a network visualization of domain expertise and factors that drive utilization of that knowledge. In this light, the authors support the view of Chong (2001) and Khan, Chong and Quaddus (1999), that implementing such an approach, ultimately constitutes a Decision Support System (DSS) – i.e. an IS "whose primary purpose is to provide knowledge workers with information on which to base informed decisions" (Mallach, 1994). However, because of this, the authors note that input and output of data, still requires expert intervention (in the guise of either the researcher or the domain expert). This is to ensure that the FCM is modeling the real-world situation effectively and within the correct context. Furthermore, there is a high degree of subjectivity involved in applying causal weightings – which again requires some level of reasoning. Conversely, FCMs are easy to draw and compute and can be formulated and modified by individuals who have little or no prior knowledge of fuzzy concepts. Crucially, the structure of an FCM defines not only input and output states (i.e. content), but also implicitly incorporates knowledge about the system in question (i.e. context). As a result, the authors now wish to highlight a number of knowledge dependencies that need to be understood in order to apply this DSS approach effectively. FCM generation is ultimately rooted in the selection, classification, codification and simulation of knowledge about a given task (in this case, ISE). As such, these four aspects bear similarity with the SECI approach of Nonaka and Takeuchi (1995) and are shown in Table 3.

| ***Knowledge Modeling Steps*** | ***FCM Steps*** | |
|---|---|---|
| | **Explicit** | **Tacit** |
| **Elicitation** | Identify decision-making scenario and experts | |
| **Codification** | Generate FCM and run simulation | - |
| **Analysis** | Elicit then refine knowledge | |
| | - | Analyze and feedback simulation results to experts |
| | Simulation (*Socialization*)<br>Selection (*Externalization*) | Codification (*Collaboration*)<br>Classification (*Internalization*) |
| | ***SECI Aspects*** | |

**Table 3. Knowledge dependencies in FCMs**

This table essentially shows the interplay between explicit (quantitative) and tacit (qualitative) knowledge. Assuming a suitable domain for FCM modeling has been chosen, explicit (factual) as well as tacit (experiential) knowledge is first of all elicited from domain experts. Following this, the researcher / fuzzy engineer then codifies this data into an FCM (i.e. making tacit knowledge also explicit as a result). Finally, in trying to explain and understand the FCM in context, explicit knowledge embodies the results of the simulation, and tacit knowledge provides reasoning behind understanding interrelationships within the mapping. Knowledge dependencies thus exist within the application of the FCM approach, in the form of an iterative cycle of shifting explicit-tacit knowledge, between knowledge elicitation, codification and analysis. A key driver for this FCM approach is the method by which knowledge is elicited from domain experts.

As the literature shows (Ford and Sterman, 1998; Rhem, 2001), this involves a deep understanding of not only the goals of the elicitation, but also the ability to recognize and filter elicited responses effectively. Eliciting and modeling knowledge not only involves the usage of a representation that is understandable and accessible by domain experts; but also, the ability to recognize and highlight patterns in knowledge coupled with the capability to resolve conflicting information under uncertainty. Hence, at each stage in the FCM generation process knowledge is required in order to harness, filter and understand the impact of system interrelationships (as shown in the approach taken by the authors). Furthermore, the inherent switching between both explicit knowledge (required to structure a system's context), and tacit knowledge (required in order to define causality and inference), is essential to communicating the output of the FCM approach.

## CONCLUSIONS

Within this paper, the authors have shown the application of Fuzzy Logic in the guise of an FCM in order to elucidate key aspects of the investment justification process, within ISE. This allowed the identification of causal relationships in this decision-making task, via an analysis of a case study organization (Company A). These FCMs were derived as a result of two models of investment justification, which involved the inclusion of Strategic, Tactical, Operational and Financial criteria; and of Project benefits, risks, costs and value respectively. The investment justification approach used by Company A was thus abstracted using this Fuzzy ISE (F-ISE) method by modeling interdependencies within the investment justification task, and generating FCM simulation results. Through applying a number of initial data, further insight into the investment justification process was provided, through an analysis of the mapping response. In the case of the STOF FCM, this view was inherently biased towards Tactical and Financial considerations, without taking Operational and Strategic views into account. In comparison, viewing the results of the functional risks and benefits model shows that this approach highlights the importance of taking project benefits, costs and risk factors into account. It was found that the consideration of project value does not adversely affect the decision-making task in any way. The authors noted that in order to apply this technique effectively, requires an understanding of explicit as well as tacit knowledge dependencies, requiring expert knowledge to model the system. This was outlined in terms of comparing key ISE and FCM steps against the well-known SECI model of Nonaka and Takeuchi (1995). In doing so, noting that there is an interplay between explicit and tacit knowledge forms in the FCM generation and analysis process. In addition, the visual nature of this technique means that it is not only a useful DSS tool, but also a powerful decision-augmenting communication tool as well (as opined by Kosko, 1990). Hence, although this paper has highlighted the application of an FCM to the topic of ISE, the authors believe further research can be carried out in terms of improving the generation of each FCM by using multiple experts; carrying out FCM simulations of equivalent ISE processes within other manufacturing organizations; and finally, investigating the usefulness of extending such fuzzy logic techniques within the DSS and wider Operational Research (OR) fields.

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