FUZZY- EXPERT SYSTEM FOR COST BENEFIT ANALYSIS OF ENTERPRISE INFORMATION SYSTEMS: A FRAMEWORK

Faith –Michael E. Uzoka
Department of Computer Science and Information Systems, Mount Royal University, Calgary, Canada

Abstract - Enterprise Information Systems (EIS) are collections of hardware, software, data, people and procedures that work together to manage organizational information resources, ultimately enhancing decision making, and strategic advantage. One of the key issues in the acquisition and utilization of EIS is the determination of the value of investment in such systems. Traditional capital budgeting models such as NPV, IRR, payback period, and profitability index focus mainly on quantifiable variables. However, there are many intangible variables that make the use of entirely quantitative measures incomplete and less inclusive. The high level of impact of information systems (IS) on the entire organizational strategy and the information intensity of IS makes the use of such traditional methods less practicable. Attempts have been made to overcome these shortcomings by utilizing other techniques such as the real options model, goal programming model, knowledge value model and intelligent techniques. This paper proposes the adoption of a hybrid intelligent technique (fuzzy-expert system) in carrying out a cost benefit analysis of EIS investment. The study takes high cognizance of intangible variables and vagueness / imprecision in human group decision making that requires a good level of consensus.

Keywords: Fuzzy logic, Expert System, Enterprise Information Systems, Cost-Benefit Analysis, MCDA, Rating Confidence.

I. INTRODUCTION

Information systems have become vital tools in organizational performance. It is observed (O'brien and Marakas 2006) that such systems create value for the firm by improving business process execution, enhancing decision making, and strategic positioning. However, there are concerns that huge investments in information systems are often difficult to justify (Hart and Webber 2002, Kumar 2004). This is because information systems fundamentally change ways by which organizations do business and affects the entire organizational structure and components (Laudon and Laudon 2005)

Most organizational decision making involve multi-criteria analysis, and fall within the realm of multi-criteria decision analysis [MCDA] (Sen and Yen 1998). MCDA situations are structured, semi-structured or unstructured (Hotmann 2006), and a huge problem arises where there is a high level of variance in parameter structure. The challenge is on how to bring the structured and unstructured variables to the same metric (TBC 1998). The determination of the cost effectiveness of enterprise information systems (EIS) is an MCDA problem with a high degree of variance in parameter structure. In order to carry out a cost benefit analysis with a good degree of parameter coverage, a number of tangible and intangible costs and benefits would have to be synthesized (Laudon and Laudon 2007)

Traditional cost benefit models such as net present value (NPV), internal rate of return (IRR), and payback period (PB) seek to adopt a monetary unit as a basis of analysis, in which all non-monetary parameters are given monetary values (TBC 1998, Tang and Beynon 2005). It is observed in (Oz 2004, Phillips-Wren *et al* 2004) that most costs and benefits associated with enterprise information systems are mostly intangible, which makes the use of traditional quantitative financial models heavily biased towards tangible costs and benefits. In an attempt to address the need to combine tangibles and intangibles in the cost benefit related decision making process, some organizations resort to evaluations based purely on expert subjective judgment. This approach has a number of pitfalls (Stamelos *et al*. 2000) such as: inability to understand completely and reproduce the results, poor explanation of decision process and associated reasoning, possibility of missing out important problem details for the evaluation, high probability of different experts producing different results without the ability to decide which one is correct, difficulty in exploiting past evaluations, and the risk of producing meaningless or highly faulty results.

In recognition of the need to have a methodical means of evaluating the costs and benefits associated with EIS that considers tangible and intangible components, with the goal of achieving a high level of completeness in variable inclusion, a fuzzy expert system (FES) is proposed. The fuzzy component addresses the vagueness associated with human judgement, especially of intangible parameters. An expert system is a computer system that applies reasoning methodologies to knowledge in an attempt to achieve a high level of performance in task areas, which for human beings require years of special education. Fuzzy expert systems incorporate elements of fuzzy logic, which is a logically consistent way of reasoning that can cope with uncertain or partial information, characteristic of human thinking (Hotmann 2006).

The aim of the study is to propose a framework for fuzzy expert system that would assist in cost benefit analysis of enterprise information systems, adopting fuzzy linguistic

 ISSN : 0975-3397

evaluation of variables. This study utilises the present 'perceived value' bypassing the time value/preference principle characteristic of conventional cost-benefit models. This is done for three reasons: 1). The proposed system utilizes linguistic values rather than monetary quantities, which is characteristic of conventional models; 2). Fluctuations in asset values resulting from time vicissitudes are difficult to model in a discounting situation especially when the 'willing to pay' principle (TBC 1998) is applied to conversion of a large number of intangibles to monetary values; 3). Costs and benefits do not occur at the same time; costs tend to be upfront and mostly tangible, whereas benefits tend to be back loaded and intangible (Laudon and Laudon 2006). The rest of the paper is structured as follows: In Section 2.0 some existing literature relating to cost benefit analysis are reviewed, while Section 3.0 presents the research methodology, which provides a full elaboration of the proposed fuzzy –expert system methodology and procedure. In Section 4.0 some concluding remarks are made, which include contributions to knowledge.

II. LITERATURE REVIEW

Computer information system (IS) has become vital in the growth and survival of organizations. In the past, the organization's key functional areas (finance, production, marketing and human resources) utilized information systems as a tool for data processing. Today, the reverse is the case, as IS has become a key driver of other functional units (Laudon and Laudon 2007). Globalization, rise in the information economy, transformation of the business enterprise, and emergence of the digital firm are major changes that have posed major challenges, necessitating huge investments in IS as a strategic tool (Kumar 2004). Information technology (IT) and IS are used interchangeably, though IS includes people and procedures. Estimates show that IT accounts for between 35 and 50 percent of total business expenditure on capital equipment in the Unites States of America (Laudon and Laudon 2005). Global investment in IT in 2003 was estimated at $852 billion and the figure rises significantly every year (Oz 2004).

A key issue has centred on justification for huge IS investment. Two approaches have been utilized in providing measures of the business value of investment in IS. These are the economic evidence and the accounting evidence (Webber 2005). The economic evidence focuses mainly on productivity (e.g. Barua et al. 1995, Dedrick et al. 2003), while the accounting evidence focuses on the impact of IS on financial performance measures such as profitability and market value (e.g. Tatcher and Oliver 2001, Im et al. 2001). A huge controversy exists as to whether IS investment increases productivity. For over a decade, researchers have been trying to quantify benefits from IS investment. The results of these studies have been mixed, and the term productivity paradox was coined to describe such findings (Laudon and Laudon 2005). While some researchers did not find any significant productivity gains (e.g. Weill 1992, Barua et al. 1995), others found significant gains in both productivity and financial performance (e.g. Brynjolfsson et al. 1999, Hitt et al. 2002, Uzoka and Chiemeke 2002, Ojedokun 2006). A key problem with the evaluation of returns on IT/IS investment is the measurement of output, which is relative according to intensity of information utilization (Dedrick et al. 2003). Another problem is the quantification of numerous highly qualitative variables (Svenningsen 1998).

Traditional capital budgeting models used in evaluating the value of investment in IS rely on cash flow measures. They assume that all costs and benefits are known, and that these costs and benefits can be expressed in a common metric – money. However, these assumptions are rarely met in the real life (Laudon and Laudon 2005). Capital budgeting models include: payback period, rate of return on investment (ROI), net present value (NPV), cost –benefit ratio (CBR), profitability index, and internal rate of return (IRR) (TBC 1998, Tang and Beynon 2005). It is observed (Laudon and Laudon 2005) that most of the traditional capital budgeting methods miss out a great deal of strategic considerations in an attempt to quantify and discount monetary units of intangibles. Hitt and Bynjolfsson (1995) argue that because of the distributive and flexible effects of IT investment on the organizational strategy and components, traditional methods of measuring returns on IT investment are misleading and inadequate, and opine that IT investments may produce productivity benefits such as increased consumer surplus without translating to profitability.

The real options pricing model (ROPM) (Benaroch and Kauffman 2000) is one of the attempts to address the shortcomings of traditional models. It recognizes the right but not the obligation to act at some future date. It differs from the financial option in that it recognizes that investment in information system would produce returns that are highly organization dependent as a result of factors such as prior expertise, skilled labour force, market conditions, etc. The disadvantage of the ROPM is that it ignores rules of thumb in information asset evaluation (McGrath and McMillan 2000). The knowledge value added model is another non traditional model, which involves focusing on the knowledge input into a business process as a means of determining the costs and benefits of changes in business processed from new information systems. The model makes some assumptions that may not be valid in all situations especially product design, research and development, where processes do not have predetermined outputs (Housel et al. 2001). The goal programming (GP) model (Schiniederjans et al. 2003) attempts to be more inclusive than traditional methods, but utilizes a complicated mechanism, which requires a prior knowledge of goal programming by the decision maker. Intelligent and soft computing techniques are becoming popular because of their ability to model human reasoning in a less complicated framework. Examples of intelligent and soft computing techniques utilized in information system studies can be found in (Stamelos et al. 2000, Phillips-Wren et al. 2004, Cochran and Chen 2005). One of the key advantages of intelligent systems or hybrid intelligent systems, such as fuzzy expert systems, is the modelling of unstructured variables and an attempt to utilize linguistic values in the evaluation process (Harmon and King 1985).

There is a high level of uncertainty management in intelligent systems. This is because human reasoning and decision making is fuzzy, involving a high degree of vagueness in evidence, concept utilization and mental model formulation

ISSN : 0975-3397

(Wang and Elhag 2006). Controversy or ambiguity in weighing objectives can also create decision uncertainty. These uncertainties reduce the optimality of decisions made by the decision makers (Morgan and Henrion 1990). Uncertainties in decision making have been analyzed from several different perspectives. Borsuk et al.(2001) adopted the probability network model to support decision in the near term under uncertainties associated with parameters, while Xu and Da (2004) applied vector projection method to uncertain multi-attribute uncertain decision making with preference information on alternatives. The use of fuzzy logic (Zadeh 1965) has become increasingly popular in addressing imprecision, and uncertainty in group decision making (Bender and Simonovic 2000)

The decision problem may be classified as choice problem, sorting problem, or ordering problem (Roy 1990 cited in Petro et al. 2005). The combination of fuzzy preference relations and Analytic Hierarchy Process (AHP) methodology in multi-criteria decision analysis (MCDA) gained prominence with the work of Van et al. (1983) which compared fuzzy ratios described by triangular membership. The fuzzy logic has been adopted in several MCDA procedures such as reported in (Buckley 1985, Cheng 1996, Wang and Lin 2003, Mikhailov and Masizana 2004, Phillips-Wren et al. 2004, Omera et al. 2005). Attempts have also been made to combine fuzzy logic with AHP and/or expert system technologies such as artificial neural networks (Stam et al. 1996, Kuo et al. 2002) and case based reasoning (Petro et al. 2005) in dealing with uncertainties in decision making. Two components present uncertainty and vagueness in an MCDA situation: 1). the rating/ranking of the relative importance of decision criteria, and 2). the rating of the decision alternatives based on the available criteria. Both components rely on the expertise, experience, and confidence of the decision experts (DEs) who rank the criteria and evaluate the alternatives. In some cases, the experts that rank the criteria may be domain experts who might be different from decision makers/managers that evaluate decision alternatives. However, in both cases, the confidence level of the expert is a critical factor in determining the optimality of the decisions especially in a group decision process (Silk 1984, Wang and Chuu 2004, Mikhailov 2004, Beynon 2005, Chen and Liu 2005). In a linear model of evaluation of alternatives $a_i(i=1,2,..,n)$ based on a set of variables $v_j(j=1,2,\ldots, m)$, each variable is assigned a weight $w_k(0\leq k\leq 1)$ in the decision process. Thus the global variable (G) of a decision alternative is $T_i(i=1,2,\ldots,p)$ is the sum of its values at the nth criteria/variables $(v_1(a_i),\ldots,v_m(a_i))$, which is given as:

$$G_1(V_j,k) = \sum_{j=1}^{m} k_j v_j \text{ , with } \sum_{j=1}^{m} k_j = 1 \quad \text{and} \quad k_j \geq 0$$

A difficult part of this decision process is the setting of values of the scaling constants k_j, since this parameter will reflect the decision makers' values and trade-offs. Key issue in weight estimation is the determination of the confidence level of such estimates. Deng et al. (2004) proposed the estimation of attribute weight through evidential reasoning and mathematical programming, which is based on weight, utility, and preference constraints. While the linear programming (LP) methodology provides an interval estimate $w(i_1 \sim i_2)$ for attribute weights, it produces non-unique solutions (weights). Shirland et al. (2003) improved on the mathematical programming methodology by applying quadratic programming (QP) in the prioritization of attributes to get unique solutions. It also provides a methodology for determining the respondents' consensus on the rating. LP and QP present complex solution methodologies that are highly mathematical and difficult to apply. A multiple regression methodology for assigning weights to attributes in an evaluation process is utilized in (Fedorowicz 1984), while factor analysis models have also been used in (Magidson and Vermunt 2004). The factor model computes the linearized loadings for each variable V_i. The loadings are used to sort the ratters according to the magnitude and direction of bias, based on parameter θ_i that shows the validity of the ratings on variable i. The use of indifference relationships is presented in (Belacel et al. 2001). It provides for the computation of an indifference index $I(a,b_i^h)$ in the interval [a,b] based on concordance and discordance indices.

While good attempts have been made at determining costs and benefits of IS investment utilizing a number of measures, it is clear that traditional financial methods have serious drawbacks, which necessitate the use of other techniques such as intelligent techniques which are very popular in the computing world. Equally, uncertainty and weight estimation measures have been developed in the past. There is need to find highly inclusive, flexible and organization friendly techniques that would evaluate costs and benefits associated with investment in IS in a team based (consensus evaluated) environment.

III. RESEARCH METHODOLOGY

The methodology of the framework follows the conventional procedure for the development of a fuzzy expert system. It integrates technologies from the fields of computer science, software engineering, knowledge engineering, and multi-media systems. The flow of the research, adapted from (Zaiyadi 2005) is shown in Figure1.

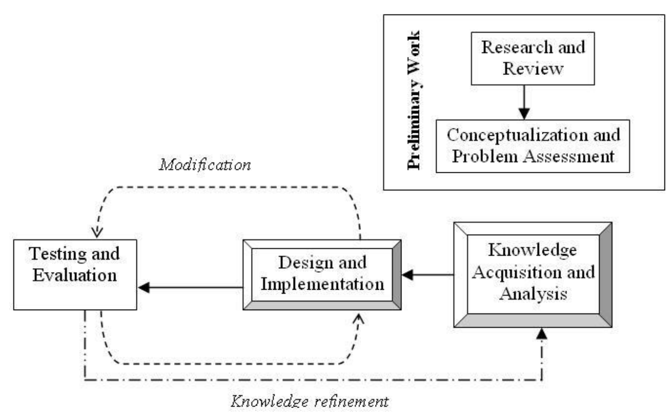

Figure 1. System's Development Framework

A. Preliminary Work

The preliminary work includes research and review, conceptualization and problem assessment. The first stage of

ISSN : 0975-3397

the study involves review of existing literature in the area of cost benefit analysis in order to identify the flaws inherent in existing models. Research is further conducted on the possibility and plausibility of development of a fuzzy-expert cost benefit system. The research further reviews underlying concepts behind the development of fuzzy expert system. This step is important as it provides some insight into the performance of expert systems and their ability to compliment human expertise in specific problem domains. The conceptualization stage identifies the fundamental and basic concept of expert system to guide in the determination of the various elements of the problem domain and the application of expert system technology in the management of identified elements.

B. Knowledge Acquisition and Analysis

The knowledge acquisition and analysis adapts the model specified in (Cochran and Chen 2005) and shown in Figure 2.

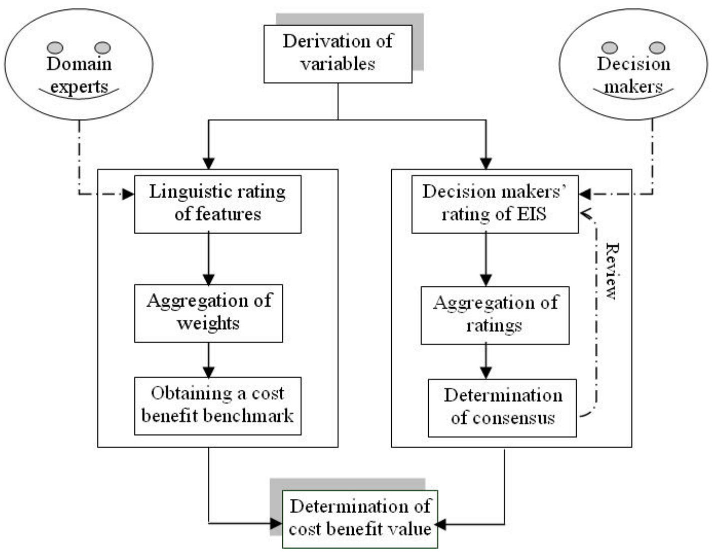

Figure 2. FES Knowledge Acquisition and Analysis

1)

3.2.1 Derivation of Variables

At the initial stage, the relevant cost-benefit variables are determined. The following knowledge acquisition procedure (Hotmann 2006) is proposed:

a. Identification of variables from existing literature on tangible and intangible cost –benefit analysis of EIS. The variables obtained from literature are shown in Appendix A.

b. Conducting a face to face interview with experts in information systems (IS) utilization and evaluation in order to identify more variables that are experiential and not contained in literature.

3.2.2 Linguistic Rating of Features

The second stage involves linguistic rating of identified cost benefit variables using a seven point likert type fuzzy query and ranking tool (Gu 2005). This is achieved through a structured questionnaire meant for IS experts and managers. The questionnaire is divided into five sections. Section A deals with demography, Section B focuses on the rating of tangibles costs, while Section C focuses on the rating of intangible costs. Sections D and E address the rating of tangible and intangible benefits respectively

3.2.3 Aggregation of Weights

This stage involves the aggregation of the rating of features using a modified fuzzy inference/aggregation methodology adapted from (Akinyokun 2002, Shirland et al. 2003, Chiou et al. 2005, Beynon 2005). The following steps are defined:

Step 1: Standardization of Experts' Rating Confidence

The essence of standardizing the rating confidence is to reduce the distance between the raw confidence values and the population mean confidence values for each of the attribute rating. Here, we utilize the theoretical population mean confidence using the sample mean confidence (Akinyokun 2002). The standardized random variable α is the expert i rating confidence for variable j, given as:

$$\alpha_{i,j} \quad = \quad C_{i,j} + \left(\frac{C_{i,j} - \overline{C^*_{i,j}}}{\sigma^*_{i,j}} \right) \text{(j=1, 2,…, p)} \qquad (1)$$

Where $C_{i,j}$ is the raw confidence associated with α, $\overline{C^*_{i,j}}$ is the mean rating confidence for n experts on variable j, while the associated variance is $\sigma^*_{i,j}$.

Step 2: Adjustment of Fuzzy Values by Standardized Rating Confidence

The experts' judgments produce fuzzy values, which represent imprecise judgments. The value is known as triangular fuzzy number, which represents a three valued judgment (Kaufmann and Gupta 1988).

Definition: A triangular fuzzy number (TFN) $\tilde{b}$ is defined by a triplet (l, m, u). The membership function is defined as:

$$\mu_{\tilde{b}}(x) \quad = \begin{cases} \frac{(x-l)}{(m-l)} & l \le x \le m \\ \frac{(u-x)}{(u-m)} & m \le x \le u \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

Because of its symmetric nature, a TFN can always be given by its corresponding left and right representation of each degree of membership.

$$\tilde{M} = [l_\alpha, u_\alpha] = [l+(m-l)\alpha, u+(m-u)\alpha] \qquad (3)$$

Where l_α and u_α are the upper and lower bounds respectively and α is the confidence level and [0≤ α ≤ 1] (Kahraman et al. 2004). The confidence level utilized in this study is the standardized rating confidence α obtained in (1)

ISSN : 0975-3397

Step3: Deriving Aggregate Fuzzy Weights

Several methods exist for derivation of aggregate fuzzy weights for each criterion i. These include the fuzzy logarithmic least square method (Boender et al. 1989), fuzzy least square method (Xu 2000), fuzzy arithmetic mean method (Cochran and Chen 2005) and fuzzy geometric mean method (Buckley 1985, Chiou et al. 2005).This study utilizes the fuzzy geometric mean method because it has the characteristic of dampening the effects of very high or low values, thereby reducing estimation bias. The fuzzy geometric mean $\tilde{w}_j$ of the jth criterion from n expert evaluators is given as follows:

$$\tilde{w}_j = (\tilde{a}_{j1} \otimes \tilde{a}_{j2} \otimes \tilde{a}_{j3} \otimes \cdots \otimes \tilde{a}_{jn})^{\frac{1}{n}} \tag{4}$$

where $\tilde{a}_{ji}$ represents the value of the subjective judgment of the importance of criterion j made by expert i obtained in (3) and (i = 1,2,…, n; j =1, 2, …, p). The operation $\otimes$ represents the multiplication operation on fuzzy numbers.

Step 4: Dufuzzification

Dufuzzification is the process of converting the fuzzy weights obtained in (4) into crisp values (Giarratano 2005). The most popular dufuzzification methods are the centre of gravity (CoG) or centroid method and the mean of maximum (MoM) method. The CoG method is proposed in this framework because it is more accurate in representing fuzzy sets of any shape (Cochran and Chen 2005). The fuzzy weights w_j obtained in (4) are triangular fuzzy sets {$\tilde{w}_j$ = (a,b,c)}. The centroid of the fuzzy triangle (a, b, c) is given as:

$$w_j = (a+b+c)/3 \tag{5}$$

where a, b, c are the lower, median, and upper fuzzy values respectively. This gives a crisp value that represents the experts' weighting of the importance of the criterion. This is normalized for the cost and benefit criteria. The normalized crisp weight for variable j given as λ_j is derived as follows:

$$\lambda_j = \begin{cases} \dfrac{w_j}{\sum_{k=1}^{g} w_{kc}} & \text{j is a cost variable [g is total number of cost variables]} \\ \dfrac{w_j}{\sum_{l=1}^{h} w_{lb}} & \text{j is a cost variable [h is total number of benefit variables]} \end{cases} \tag{6}$$

$$\sum_{k=1}^{g} \lambda_j^k = 1 \quad \text{and} \quad \sum_{l=1}^{h} \lambda_j^l = 1$$

Where λ_j^k is a cost variable weighting and λ_j^l is a benefit variable weighting

3.2.4 *Obtaining a Cost Benefit Model*

A cost benefit expert system model is obtained based on the value of λ_j obtained in (6) and the ES technology described in Section 3.4. In order to determine the cost effectiveness (or otherwise) of an organization's EIS, the aggregate Euclidean distance between the normalized cost and benefits weights obtained in (6) and the normalized cost and benefits decision makers' evaluation of the information system (described in Section 3.2.5) are computed. The Euclidean distance is the 'ordinary' distance between two points, which can be proven by repeated application of the Pythgorean theorem. In this analysis, the Euclidean distances between the normalized criterion weight λ_j and normalized aggregated decision makers' criterion rating of the EIS r_j are given as follows:

$$C_d = \sqrt{\sum_{j=1}^{g} (r_j - \lambda_j)^2} \tag{7}$$

$$B_d = \sqrt{\sum_{j=1}^{h} (r_j - \lambda_j)^2} \tag{8}$$

Where C_d and B_d are the values of the Euclidean distance evaluation of aggregate cost and benefit respectively.

The decision rule is:

$$\text{If } \begin{cases} C_d > B_d & \text{EIS is not cost effective} \\ B_d > C_d & \text{EIS is cost effective} \\ B_d = C_d & \text{Indifference} \end{cases}$$

3.2.5 *Decision Makers' Rating of Organization's EIS*

The fuzzy expert system takes inputs of organizational decision makers (DM) on the rating of the EIS based on the variables that have been weighted by the domain experts (DE). It is important to note that the DEs are drawn from different organizations, but the DMs are members of the organization whose EIS is being evaluated. Evaluation of the organization's EIS by a group of DMs raises two key issues:

a. Assessment of the degree of consensus of among the decision makers in the rating process.

b. Aggregation of group members' ratings, taking cognisance of the varying levels of importance of group members in the decision process.

3.2.5.1 *Aggregation of Decision Makers' Ratings*

The procedure for aggregation of decision makers' weights will be the same as stipulated in Section 3.2.4. However, the level of importance of the decision maker in the organization

ISSN : 0975-3397

would be modelled in the decision process. A key challenge of this framework would be to find such appropriate modelling of the degree of importance of the DM in the organization's decision matrix. Importance of an individual could be determined by his experience, position, tasks performed, expertise, relevance of qualifications to the specific decision making, level of stake-holding and other factors, which are highly unstructured.

3.2.5.2 Measuring Degree of Consensus

It is important to confirm that the results obtained from the evaluation of EIS by DMs have a high degree of group consensus, which in turn increases the validity of the evaluation (Chen and Liu 2006). If the consensus is below a certain threshold, then it is suggested that the group members re-evaluate the EIS under an adjusted evaluation environment that could promote consensus. A measure of group consensus is presented in (Shirland et al. 2003). The degree of agreement between individual evaluation of EIS and group evaluation for all DMs is measured by:

$$\delta_i = \sqrt{\sum_{j=1}^{p}(r_{ij} - r_j^*)^2 / p} \quad \text{for } i=1,2,\ldots,n \quad (9)$$

where r_{ij} is the rating on attribute j by DM i, r_j^* the group rating on attribute j for all DMs, p is the number of attributes and n is the number of DMs.

If the individual attribute ratings by DM i are identical with the group ratings, then δi will be zero. As the extent of agreement decreases, δi will increase accordingly but will not equal or exceed a value $\delta_i^{max}(n)$. This upper limit on δi is determined as follows:

$$\delta_i^{max}(p) = \sqrt{(1/3)(p+1)(p-1)} \quad \text{for } i=1,2,\ldots,n \quad (10)$$

The overall degree of consensus for the entire group is given by:

$$\delta = \sqrt{\sum_{i=}^{n}\delta_i^2 / n} \quad (11)$$

If all n respondents agree on p attributes ratings, δ will be zero, and the group ratings will all equal (p+1)/2. As consensus decreases, δ will increase accordingly but will not exceed the value of $\delta^{max}(p)$. If it does, then the evaluation should be redone as there is no consensus. The upper limit of $\delta^{max}(p)$ is given by:

$$\delta^{max}(p) = \begin{cases} \sqrt{(1/12)(p+2)(p+1)-(1/4)(p+1)} & \text{for } p=2,4,6,\ldots \\ \sqrt{(1/12)(p+1)(p-1)} & \text{for } p=1,3,5,\ldots \end{cases} \quad (12)$$

Since δ=0 indicates complete consensus and δ=$\delta^{max}(n)$ indicates complete disagreement, the overall level of consensus can be expressed as

$$\psi = 1-(\delta/\delta^{max}(p)) \quad (13)$$

3.3 Design and Implementation

The analyses performed in Section 3.3 leads to the design and implementation phase of Figure 1, which utilizes the expert system methodology. The expert system (ES) architecture is presented in Figure 3 (Zaiyadi 2005, Uzoka and Akinyokun 2005, Hotmann 2006, O'Brien and Marakas 2007).

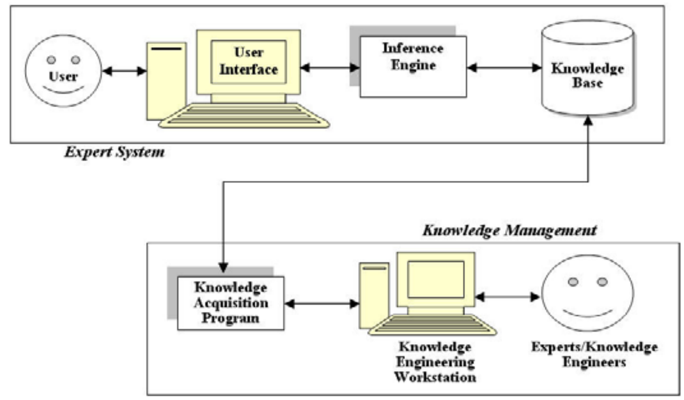

Figure 3. The Expert System Architecture

The knowledge management system utilizes the procedure specified in Section 3.3 to acquire expert's knowledge on the cost-benefit elements of organization's enterprise information systems. The expert system contains the following elements:

a. Knowledge base

b. Inference engine

c. User interface

The knowledge base is an assembly of all the information and knowledge (facts, rules, and procedures) about a subject domain. The rules and procedures are mainly heuristics (rules of thumb) that express the reasoning process of an expert on the subject domain. There are many ways in which knowledge is represented in an expert system. These include rule-based, frame-based, object-based, and case based methods of knowledge representation. This framework proposes the frame-based method because it provides a natural way for the structured and concise representation of knowledge (Negnevitsky 2002). A frame is a collection of knowledge about an entity consisting of a complex package of data values describing attributes (O'Brien and Marakas 2007).

The inference engine processes the data in the knowledge base in order to arrive at logical conclusions (Hotman 2006). There are two commonly used inference strategies – the forward chaining strategy and the backward chaining strategy (Laudon and Laudon 2007). In the forward chaining (data driven) strategy, the inference engine uses production rules to deduce a problem solution from an initial input data; while in the backward chaining (goal driven) strategy, the inference engine uses production rules to break a goal into smaller sub-goals which are easier to prove. It starts with a hypothesis and proceeds by asking the user questions about selected facts until the hypothesis is either confirmed or disproved. This

ISSN : 0975-3397

framework adopts the forward chaining strategy because it is data driven analysis. The results obtained in Section 3.2.3 are used as benchmarks, while the evaluations obtained in Section 3.2.5 are measured against the benchmark according to the procedure set out in Section 3.2.4 in order to arrive at the cost-benefit comparison of an organization's EIS.

The user interface would be based on the menu-driven facility of any visual programming Language linked to an expert system programming language. A top down design is supported and access is gained by supplying user name and password, both of which aid the control of access. Each submenu calls the associated inference procedure, which is interactive. It is either menu-driven or guides the assessor intelligently to supply appropriate information. The user interface also accommodates an explanation facility, which explains the reasoning behind the expert system's decision reasoning process.

4 CONCLUSION

This framework proposed in this paper utilizes intelligent technologies to develop a methodology that would assist enterprise information system users, managers and entrepreneurs in analysing cost-benefit of EIS. The cost-benefit analysis would assist in determining the worthiness (or otherwise) of investment in IS. There are difficulties in analyzing cost-benefit because of highly unstructured nature of IS evaluation variables. This paper proposes a framework for the inclusion of the unstructured variables in an IS CBA model. It also makes a rigorous effort at providing a platform for inclusion of rating confidence of domain experts and decision makers in the EIS evaluation matrix in a consensus based environment.

The following are the contributions of the proposed system to existing literature on cost-benefit analysis of enterprise information system: 1). It is be a major attempt at identifying a comprehensive list of intangible costs and benefits associated with acquisition, utilization, and maintenance of enterprise information systems; 2). Previous cost benefit models have attempted to quantify qualitative EIS cost benefit variables. This framework recognizes the skew towards qualitative variables, and suggests the qualification of quantitative variables using fuzzy linguistic variables; 3). This study adds to the existing literature in the use of fuzzy expert systems for organizational decision making. However, it is a major attempt at incorporating rating confidence at both the level of DE and DM in the processes of knowledge engineering and utilization; 4). This study recognizes group consensus in the decision making process. It also recognizes the relative degree of importance of the DM in the decision making process.

References

[1] Akinyokun O. C. (2002); Neuro-Fuzzy Expert System for Human Resource Performance Evaluation. *First Bank of Nigeria Plc Endowment Fund Public Lecture, Series 1*, Federal University of Technology, Akure, Nigeria.

[2] Balacel, N. Vicke, P. Scheif, J. M. and Boulassel M. R.(2001); Acute leukaemia diagnosis aid using multicriteria fuzzy assignment methodology. *Computer methods and programs in Biomedicine,* 64:145-151

[3] Barua A., Kriebel C.H. and Mukhopadhyay T. (1995); Information technologies and business value: An analytic and empirical investigation. *Information Systems Research*, 6(1): 3-23

[4] Bender M. J. and Simonovic S. P. (2000); A fuzzy compromise approach to water resource systems planning under uncertainty. *Fuzzy sets and Systems*, 115(1):35-44

[5] Borsuk, M. Clemen, R. Maguire, L and Reckhow K. (2001); Stakeholder values and scientific modelling in the Neuse river. *Group Decision and Negotiation*, 10: 355–373

[6] Beynon M.J. (2005); A method of aggregation in DS/AHP for group decision –making with the non-equivalent importance of individuals in the group. *Computers and Operations Research*, 32:1881-1896

[7] Boender C. Degran J. and lootsma F. (1989); Multi-criteria decision analysis with fuzzy pairwise comparisions. *Fuzzy sets and systems*, 29: 1330-143

[8] Benaroch M and Kauffman R. J. (2000); Justifying electronic banking network expansion using real option analysis. *MIS Quaterly;* 24(2): 197-225

[9] Brynjolfsson E. and Hitt L. M. (1998); Beyond the Productivity Paradox. *Communications of ACM,* 41 (8) 49-55

[10] Buckley J.J. (1985); Fuzzy hierarchical analysis. *Fuzzy Sets and Systems*, 17(3): 233-247

[11] Chen J. and Liu Y. (2005); A model and its application for uncertainty in group decision making. *World Journal of Modelling and Simulation*, 2(1):45-54.

[12] Cheng C. (1996); Evaluating naval tactical missile systems by fuzzy AHP based on the grade value of membership function. *European Journal of Operational Research*, 95:649-655

[13] Chiou H. Tzeng G. and Cheng D. (2005); Evaluating sustainable fishing development strategies using fuzzy MCDM approach. *Omega*, 33:223-234.

[14] Cochran J.K. and Chen H. (2005); Fuzzy multi-criteria selection of object oriented simulation software for production system analysis. *Computers and Operations Research*, 32:153-168

[15] Dedrick J. Gurbaxani V. and Kraemer K.L. (2003); Information technology and economic performance: A critical review of the empirical evidence. *ACM computing surveys*, 35(1):1-28

[16] Deng, M. Xu, W. and Yang J. (2004); Estimating the attribute weights through evidential reasoning and mathematical programming. *International journal of information technology and decision making*, 3(3):419-428

[17] Fedorowicz J. (1984); Database evaluation using multiple regression techniques.. *Proceedings of the 1984 ACM SIGMOD International Conference on Management of Data*, Boston, Massachusetts, :70-76

[18] Giarratano J.C. and Riley G.D. (2005); *Expert systems: Principles and programming (4th Ed)*. Canada: Thomson course technology.

[19] Gu L. (2005); Web shopping expert systems using new interval type-2 fuzzy reasoning. *Master of Science thesis, Georgia State University, USA*

[20] Harmon P. and King D. (1985); *Artificial Intelligence in Business: Expert Systems*. Canada: John Wiley & Sons.

[21] Hitt L. M., and Brynjolfsson E. (1995). Productivity, Business Profitability and Consumer Surplus: The three different measures of information technology value. *MIS Quaterly*; 20 (20):121-142

[22] Hotmann E. (2006); Decision support expert system for process selection. *PhD Thesis, Department of Computer Science and Mathematics*, *University of Paderborn*

[23] Housel T. J., Omar E. I. S, Jianfang J. Z. and Waymond R (2001); Measuring the return on e-business initiative at the process level: The knowledge valued approach. *International Conference on Information Systems*; Hawaii.

[24] Huang M., Wang J., Yu S., and Chiu C. (2004);Value-added ERP information goods: economic analysis. *Industrial Management and Data Systems*, 104(8):689-697.

ISSN : 0975-3397

[25] Im K.S., Dow K.E. and Grover V. (2001); Research Report: A re-examination of IT investment and market value of the firm – An event study methodology. *Information Systems Research*, 12(1):103-117.

[26] Kaufmann A. and Gupta M.M (1988); *Fuzzy mathematical models in engineering and management science*. Amsterdam, Netherlands: Elsevier

[27] Kahraman C., Cebeci U. and Ruan D. (2004); Multi-attribute comparison of catering service companies using fuzzy AHP: The Case of Turkey. *International Journal of Production Economics*, 87: 171-184.

[28] Kumar R. L. (2004); A Framework for assessing the business value of information technology infrastructure. *Journal of Management Information Systems*, 21(2):11-32.

[29] Kuo R.J., Chi S.C. and Kao S.S. (2002); A decision support system for selecting convenience store location through integration of fuzzy AHP and artificial neural network. *Computers and Industry*, 47(2):199-214

[30] Laudon K.C. and Laudon J.P. (2007); *Essentials of Management Information Systems: Managing The Digital Form (6th Ed)*. New Jersey, USA: Prentice Hall.

[31] Magidson J. and Vermunt. (2004); Latent class models. Kaplan D. (ed). *The Sage Handbook of Quantitative Methodology for the Social Sciences*, Chapter 10: 175-198. Thousand Oakes: Sage Publications

[32] McGrath, R.G. and MacMillan, I.C. (2000). Assessing Technology Projects Using Real Options Reasoning. *Research- Technology Management* 43 (4): 35-49.,

[33] Mikhailov L. and Masizana A. (2004); Decision Support for Information Systems Selection. *IEEE;* 5044-5049

[34] O'Brien J.A. and Marakas G.M. (2007); *Enterprise Information Systems (13th Ed).* Boston, USA: McGraw-Hill International.

[35] Ojedokim A. A. (2006); The Impact of Computerization on Productivity in Botswana: a case study of two state corporations. PhD thesis, Department of Library and Information Studies, University of Botswana

[36] Omera, M. D'Ambrosio, L. Pesent, R. and Ukovich W.(2005); Multiple-attribute decision support system based on fuzzy logic for performance assessment. European Journal of operational research, (160):710-725

[37] Oz E.(2004); *Management Information Systems* (4th Ed) Massachusetts: Thomson Course Technology

[38] Negnevitsky M. (2002); *Artificial intelligence: A guide to intelligent systems (2nd Ed)*. England: Addison Wesley.

[39] Petro, J. S. Burstein, F. and Sharp A. (2005); A case-based fuzzy multicriteria decision support model for tropical cyclone forecasting. *European Journal of operational research*, 160:308-324

[40] Phillips-Wren G.E., Hahn E.D. and Forgionne G.A. (2004); A Multiple Criteria Framework for Evaluation of Decision Support Systems. *Omega*, 32:323-332

[41] Schiniederjans M.J. and Hamaker J.L.(2003); A new strategic information technology investment model. *Management Decision*, l 4(1):7-8.

[42] Sen P. and Yang J.B (1998); *Multiple criteria Decision Support Systems in Engineering Design.* New York: Springer

[43] Shirland L.E., Jesse R.R., Thompson R.L. and Iacovou C.L. (2003); Determining attribute weights using mathematical programming. *Omega*, 31:423-437

[44] Silk J. B.(1984); Measurement of the relative importance of individual selection and kin selection among females of the genus macaca. *Evaluation*, 38(3): 553-559

[45] Stair R. and Reynolds G.(2006); *Principles of Information Systems (7th Ed).* Massachusetts: Thomson Course Technology.

[46] Stam A. Minghe S., and Haines M. (1996); Artificial neural network representations for hierarchical preference structures. *Computers and Operations Research*, 23(2):1191-1201.

[47] Stamelos, I. Vlahavas, I. Refanidis, I. and Tsoukias A. (2000); Knowledge based evaluation of software systems: a case study. *Information software technology*, 42:55, 333-345

[48] Svenningsen K.(1998); An evaluation model for electronic resources utilizing cost analysis, The Bottom Line. *Managing Finances*, 11(1):18 – 23.

[49] Tang Y. and Beynon M. J.(2005);Application and development of Fuzzy Analytical Hierarchy Process within a capital Investment Study. *Journal of Economics and Management*, l(2):207-230.

[50] Tatcher M.E and Oliver J.R. (2001); The impact of technology investment on a firm's production efficiency , product quality and productivity. *Journal of Management Information Systems*, 18(2): 17-45.

[51] TBC[Treasury Board of Canada] (1998); Benefit cost analysis guide. Downloaded on February 2007 from http://www.tbs-sct.gc.ca/fin/sigs/revolving_funds/bcag/bca2_e.asp.

[52] Turunen P. and Salmela H. (2006); The cost benefit approach to medical Information systems evaluation. Downloaded on 23 February 2006 from www:tucs.fi/publications/techreports.

[53] Uzoka F.M.E and Akinyokun O.C. (2005); Knowledge Base System for Human Resource Evaluation in a University Environment. *Journal of Testing and* Evaluation, 33(1):1-8

[54] Uzoka F.M.E. and Chiemeke S.C. (2002); The Impact of Information Technology on Productivity in Government Parastatals. *The Nigerian Journal of Research and Production*, 2(2):107-113

[55] Van P.J.M., Arhoven A. and Pedrycz W.A. (1983); Fuzzy extension of Saaty's priority theory. *Fuzzy Sets and Systems*, 11(3):229-241.

[56] Wang R. and Chuu S. (2004); Group decision-making using a fuzzy linguistic approach for evaluating the flexibility in a manufacturing system. European Journal of operational research, (154):563-572

[57] Wang J. and Lin W. (2003); A fuzzy multicriteria group decision making approach to select configuration items for software development. *Fuzzy sets and Systems,* 134:343-363.

[58] Wang Y. and Elhag T. M. S. (2006); On the normalization of interval and fuzzy weights. *Fuzzy sets and systems,* 157:2456-2471

[59] Webber R. and Hart M.L. (2002); The shareholder-wealth effects of information technology infrastructure investments in South Africa. *Investment Analysis Journal*, (62):43-53.

[60] Weill P. (1992) The relationship between investment in information technology and firm performance: a study of the value manufacturing sector. Information Systems Research, 3(4): 307-358

[61] Whitman M.E and Mattord H.J. (2005); *Principles of Information Security(2nd Ed)*. Canada: Thomson Course Technology.

[62] Xu R. (2000); Fuzzy least squares priority method in Analytic Hierarchy Process. *Fuzzy Sets and Systems*, 112:395-404.

[63] Xu Z. and Da Q. (2004); Projection method for uncertain multi-attribute decision making with preference information on alternatives. International journal of information technology and decision making, 3(3):429-434

[64] Zadeh L. A.,(1965); Fuzzy Sets. *Information and Control*, 165, 8(3) 338-353.

[65] Zaiyadi M.F.B. (2005); Expert system for car maintenance and troubleshooting. *Generation5*. Downloaded on February 27 2007 from http://www.generation5.org/content/2005/CarMaintenance.asp.

ISSN : 0975-3397

APPENDIX A: EXPERIMENTAL VARIABLES

The following experimental variables, which were generated from literature, consist of tangible and intangible costs and benefits associated with enterprise information system.

Tangible costs:

- Hardware cost;
- Software cost;
- Telecommunications cost;
- License fees;
- Personnel cost;
- Computer resources cost;
- Operating cost;
- Maintenance cost

Intangible costs:

- the impact of non-compliance with registration;
- impaired knowledge management which is intensified by decentralized operations;
- diminished corporate memory which is compounded by administrative change and high staff turnover;
- the impact of not achieving best practice standards, therefore not complying with the International Standards Organization Records Management Standard (ISO 15489)
- the impact of not achieving best practice standards and information management;
- reduced accountability in decision-making and actions; and
- reduced organization productivity.

Tangible benefits:

- increased productivity;
- lower operational costs;
- reduced workforce;
- lower computer expenses;
- lower outside vendor costs;
- lower clerical and professional costs; and
- reduced facility costs.

Intangible benefits:

- improved asset utilization;
- improved resource control;
- improved organizational planning;
- increased organizational flexibility;
- legal requirements attained;
- increased organizational learning;
- enhanced employee goodwill;
- better corporate image;
- higher client satisfaction;
- improved decision making;
- improved operations; and
- increased job satisfaction.

ISSN : 0975-3397