DEVELOPING METRICS FOR DETERMINING KNOWLEDGE MANAGEMENT SUCCESS: A FUZZY LOGIC APPROACH

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ABSTRACT

Senior management may feel that knowledge management is an enigma. Part of the problem has dealt with finding ways to better measure the success of the knowledge management initiatives in the organization. As we are dealing with intangible assets, management may have some difficulty in determining why they should invest money in knowledge management versus putting the dollars towards more tangible projects. This paper discusses this perception through the use of applying fuzzy logic for developing metrics for determining knowledge management success.

Keywords: knowledge management, metrics, fuzzy logic

INTRODUCTION

According to French Caldwell, Gartner Group Vice President and Research Director, "knowledge management (KM) has reached a state of maturity and productivity that cannot be denied" [1]. Caldwell further elaborates that "successful KM programs that contribute to bottomline results can be found in all industry sectors" [1]. In spite of these successes, however, there are still many KM programs that fail after one or two years, and those that are successful may take five years or more to become entrenched within the organization [1].

Part of the reason for possible failure of knowledge management initiatives and management's skepticism towards KM is due to the inability to develop metrics to measure KM success. Knowledge management deals with intangible assets, and it may be difficult to measure the human capital, structural capital, and relationship capital in the organization. Some companies, like Skandia, Dow Chemical, and others, have been able to compute concrete dollar savings relating to their intellectual capital assets [2,11,9]. Not-for-profit organizations are also developing metrics to measure knowledge management performance. The U.S. Navy [2001], for example, through the work of Susan Hanley formerly at Dell, has developed KM performance measures as shown in Figure 1. However, the challenge is that KM deals with intangibles which are often difficult to quantify, yet management wants to know the "bottomline" in terms of the value-added benefits derived from the KM initiative. Due to the complexity in determining such "hard" metrics, many people tend to use "soft" measures, such as anecdotes or organizational narratives, to explain the usefulness and utility of their organization's KM system.

Figure 1. Summary of KM Performance Measures: Personnel and Training [16]

Business Objectives:
- Improve ability to attract and retain talent
- Enhance learning opportunities
- Improve quality of life

Common measures: These measures can be used for all KM initiatives:

Output:
- Usefulness survey
- Anecdotes

System:
- Latency (response times)
- Number of downloads
- Number of hits to the site
- Dwell time per page or section
- Usability survey
- Frequency of use
- Navigation path analysis
- Number of help desk calls
- Number of users
- Frequency of use
- Percentage of total employees using system

KM Initiatives	**Systems Measures**	**Output Measures**	**Outcome Measures**
Portal • For HR functions	• **Common Measures** • Searching precision and recall • Usage of personalization features • Frequency of general search versus use of predefined links • Number of users with the portal as their "home page"	• **Common Measures** • Printed communications cost (reduced costs for printed newsletters) • Time spent "gathering" information	• Reduced time to find relevant information • Reduced training time or learning curve (if portal is used to integrate multiple separate systems)
Communities of Practice • Ex-patriots • People who are involved in a change of duty station • Functional by expertise	• **Common Measures** • Number of contributions • Frequency of update • Ratio of the number of members to the number of contributors (conversion rate) • Number of members	• **Common Measures** • Number of grievances • Attrition or Turnover rate • Ratio of number of offers extended to number of offers accepted for employment	• Decreased attrition or turnover rate • Increase in number offers to number of accepted offers of employment • Increased employee satisfaction • Savings and/or improvement in organizational quality and efficiency
e-Learning	• **Common Measures** • Number of courses taken/user	• **Common Measures** • Training costs	• Savings and/or improvement in organizational quality and efficiency • Improved employee satisfaction • Reduced cost of training

In examining the literature [e.g., 2, 9, 11, 10], we can identify the key factors why organizations embark on KM initiatives, as synthesized and categorized as follows, in Figure 2:

Figure 2. Key Factors for Embarking on Knowledge Management Initiatives

Adaptability/Agility:
- Anticipate potential market opportunities for new products/services
- Rapidly commercialize new innovations
- Adapt quickly to unanticipated changes
- Anticipate surprises and crises
- Quickly adapt the organization's goals and objectives to industry/market changes
- Decrease market response times
- Be responsive to new market demands
- Learn, decide, and adapt faster than the competition

Creativity:
- Innovate new products/services
- Identify new business opportunities
- Learn not to reinvent the wheel
- Quickly access and build on experience and ideas to fuel innovation

Institutional Memory Building:
- Attract and retain employees
- Retain expertise of personnel
- Capture and share best practices

Organizational Internal Effectiveness:
- Coordinate the development efforts of different units
- Increase the sense of belonging and community among employees in the organization
- Avoid overlapping development of corporate initiatives
- Streamline the organization's internal processes
- Reduce redundancy of information and knowledge
- Improve profits, grow revenues
- Shorten product development cycles
- Provide training, corporate learning
- Accelerate the transfer and use of existing know-how
- Improve communication and coordination across company units (i.e., reduce stovepiping)

Organizational External Effectiveness:
- Reach to new information about the industry and market
- Increase customer satisfaction
- Support e-business initiatives
- Manage customer relationships
- Deliver competitive intelligence
- Enhance supply chain management
- Improve strategic alliances

Since KM is a "fuzzy" area and serious anecdotal evidence [5] is chiefly used to measure KM success, fuzzy logic concepts could be applied to generate a fuzzified set of metrics to measure KM success. Firestone [6,7] discusses the feasibility of using fuzzy logic to estimate the benefits of KM initiatives, and concludes fuzzy logic can help in performing measurement modeling. Chan et al. [4] describe a conceptual model of performance measurement for supply chains using fuzzy logic. Ammar et al. [1] discuss a fuzzy knowledge-based system for assessing the financial condition of public schools. Hope and Gittins [8] apply fuzzy logic to interpret qualitative data for measuring effectiveness of Extreme Programming (XP). Shore and Venkatachalam [14] evaluate the information sharing capabilities of supply chain partners through a fuzzy logic model. McIvor et al. [12] apply fuzzy logic to support financial analysis in the corporate acquisition process. Sun and Finnie [15] apply a fuzzy logic approach to experience-based reasoning.

From the references above, fuzzy logic seems to be a reasonable approach to explore for determining effectiveness measures. The research presented in this paper will address the use of fuzzy logic as a novel approach to developing metrics for measuring knowledge management success.

THE BASICS OF FUZZY LOGIC

Fuzzy logic has its roots from 1965 when Professor Lotfi Zadeh from the University of California-Berkeley, developed this approach to deal with "uncrisp reasoning." Uncrisp reasoning deals with vagueness, such as the proposition that Jay is tall. Different people may have varying opinions as to what tall means to them from their own cultural perspective. To compensate for these differences, one may create a fuzzy set to account for tallness. For example, we could use the following table to represent tallness:

Tall	Degree of Membership
5'0"	0.00
5'4"	0.10
5'8"	0.35
6'0"	0.50
6'4"	0.82
6'8"	0.98
7'0"	1.00

From the table above, a height of 6'0" has a degree of membership of 0.50. A fuzzy set is any set that allows its members to have different grades of membership (membership function) in the interval [0,1]. We can use these fuzzy sets to perform combinations. The intersection of two fuzzy sets is the minimum of the two individual membership functions. The union is the maximum of the truth of the propositions—that is, the union of the fuzzy subsets cannot be less than the membership of either component [13].

This issue of fuzziness or uncrisp reasoning is readily apparent in the combination of IF-THEN rules, often used in expert systems development. For example, assume that two of the rules in the knowledge base of an expert system, used to help us decide where to live, are as follows:

IF cheap apartments in Paris THEN rare.
IF rare THEN expensive.

When combining these rules, the result is: IF cheap apartments in Paris THEN expensive. How can <u>cheap</u> apartments be <u>expensive</u>? Perhaps, cheap apartments in Paris when compared with cheap apartments in other cities may indeed be expensive, relatively speaking. Here one can see the concept of uncrisp reasoning and the need to account for this fuzziness.

With respect to fuzzy logic, the following conclusions have been made in the literature [13]:

- Rules can be derived automatically from verbal models manipulated by semantic systems;
- If the system internalizes facts and evaluations, the inference mechanism is given by the logic of evaluations;
- If the system internalizes facts, rules, and evaluations, the inference mechanism is given by the rules interpreted as relations between fuzzy sets;
- When knowledge is captured in natural language, linguistic variables are modeled as fuzzy sets, and the internalized logic of fuzzy sets governs evidence combinations.

APPLYING FUZZY LOGIC TO KNOWLEDGE MANAGEMENT SUCCESS MEASURES

Anecdotally, one often hears that "the knowledge management initiative improves employee morale." This is a fuzzy proposition. We can apply fuzzy set theory to develop the relationship that:

Employee morale: Employee interaction→[0,1] where the domain of "employee morale" is employee interaction, and [0,1] is the co-domain of the target.

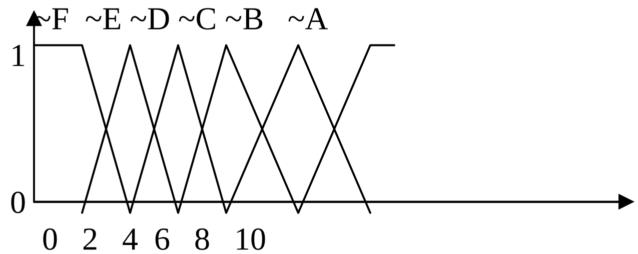
We can say that:

Employee morale={(employee interaction, degree)}: degree is the employee morale based upon the perceived image of employee interaction.

We can now create a fuzzy set as follows:

Employee Interaction	Degree of Membership
No interaction ("F")	0.00
People asking other employees to join them for lunch ("E")	0.20
Employees are sharing knowledge within departments ("D")	0.40
Employees are sharing knowledge with others across departments ("C")	0.60
Communities of practice are flourishing ("B")	0.80
All employees are connected with everyone else in the org ("A")	1.00

Evaluators of the knowledge management system can judge the success of the knowledge management initiative on improving employee morale through looking at employee interaction. We can create a fuzzy "employee morale" set by determining that an "A" grade would be "all employees are connected with everyone else in the organization" and an "F" grade is "no interaction." We can create a triangular fuzzy grade where 10 is the best score as shown below and the employee morale set is in the form of a fuzzy vector EM={A,B,C,D,E,F}[4]:



Following Chan et al. [4], we can compute an employee morale score as follows:

~A=T(8,10,10)
~B=T(6,8,10)
~C=T(4,6,8)
~D=T(2,4,6)
~E=T(0,2,4)
~F=T(0,0,2)

The employee morale set EM(μ)={(pX(μ),μ),X=A,B,C,D,E,F} where pX(μ) is the degree of belongingness or membership value of μ in EM. Let's assume that four evaluators give their respective opinions, and varying weights, as to the overall employee morale in the organization based upon focus group interviews. These weights should be normalized to add up to 1. We can compute EM(μ) by using a weighted averaging method (i.e., multiplying the measurement result matrix with the weight vector), where after these results are in the forms of fuzzy sets which can be defuzzified into a crisp value from ten to zero [4]. The defuzzified crisp number, would be the computed employee morale score, which incorporates the fuzzy sets and the opinions of the evaluators.

SUMMARY

Knowledge management practitioners should apply fuzzy logic to help quantify and measure knowledge management success. Instead of hearing "anecdotal evidence," senior management wants to know how to convert these soft measures into hard measures. Fuzzy logic may be a useful and novel approach for accomplishing this task.

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