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ABSTRACT

This paper applies Fuzzy Composite Programming (FCP), which is a Multiple Criteria Decision Making (MCDM) model, to comprehensively assess the organizational effectiveness of knowledge management strategy (KMS) of 15 clinical nursing units in a large metropolitan area hospital. FCP allows the integration of qualitative and quantitative data and provides a better decision model for assessing complex scenarios like KMS. The knowledge capabilities model, which measures the contribution of infrastructure and process capabilities on the organizational effectiveness of KM was used in conjunction with a construct to measure perceived patient benefits and risks. Additional quantitative data on the operational effectiveness of KM was collected to complete the FCP model. By fitting the FCP model using the quantitative data, we found that knowledge process capability plays the most important role in assessing Organizational Effectiveness compared to the other second level indicators. Among third level indicators, knowledge application process capability was the largest contributor to the knowledge process capability.

Keywords

Healthcare, Knowledge Management Strategy (KMS), Multiple Criteria Decision Making (MCDM), Fuzzy Composite Programming (FCP).

INTRODUCTION

Increasingly organizations are adopting knowledge management systems to achieve organizational goals. In the business context, knowledge is defined as any information that is relevant, actionable and is based on a person's experience (Davenport and Prusak, 2000). Systems, policies, processes and procedures used to manage the creation, storing, sharing and reuse of knowledge fall into the category of knowledge management systems.

Recently, health care organizations have started adopting information technologies (IT) and processes for KMS. There has been an exponential growth in the medical information available to clinical practitioners. Roughly 400,000 new entries are being added annually (Dwivedi, et. al., 2003). It would take a medical practitioner 550 years to catch up with a year's worth of entries. New research, which can dramatically influence the quality of patient care, is going unused due to the lack of clinical KM that would help practitioners to optimize their learning time. Healthcare must be recast in a new mold by applying the concept of knowledge management to bring best practices and more formal and efficient clinical practice into the picture. KM can allow physicians and nurses to play a broader role and promote self-care by patients and their compliance with treatment to stem the massive growth of health care costs.

It has been difficult convincing healthcare professionals to adopt such systems and processes in their practice (Anderson, 1997). However, the potential benefits of using KMS in the health care setting are quite promising: increasing the patient flow, reducing the number of days of excess hospitalizations, reducing costs through the translation of medical advances into clinical practice, such as patient records analysis and use of medical technological information (Hill, 2001). Therefore, there is a need for a formal assessment in healthcare organizations to rank the successful components of clinical knowledge management strategy, systems and processes that result in improved organizational effectiveness.

RESEARCH GOAL

The goals of this research are:

1. To develop a Fuzzy Logic decision-making model to assist evaluation of KMS in healthcare organizational units.
2. To achieve a better understanding of the most important factors contributing to the organizational effectiveness of KM in the clinical nursing units
3. To measure the effectiveness and operational impacts of KM in fifteen functional units in a large metropolitan area hospital.
4. To measure the nurse's perception of KM, which very few previous studies have done.

INFORMATION TECHNOLOGY IN HEALTH CARE

The health care industry is a vital element of the economy. With the aging of the US population and the rising cost of health care services, more and more health care organizations are looking to utilize Information Technology to achieve operational excellence (Grimson et al. 2000). The earlier focus of this IT adoption in health care has been mainly for cost containment, facilitation of team care and to adopt evidence-based medicine or best practices. A relatively new development is eHealth, which is IT facilitation of the actual clinical practice of health professionals using KM (Wilson, 2003). Enterprise systems and technology to enable this clinical KMS include Customer Relationship Management (CRM), Enterprise Resource Planning (ERP), Enterprise Application Integration (EAI), web services, workflow, web portals, EDI, data bases for patient records, PDA's, etc. (Amolat and Dragon, 2002).

Health Care IT spending is currently growing at 3.8% year over year as reported by Brown (2003). This study also found from surveys of hospitals, that key goals of the IT adoption by the healthcare organizations are to lower costs, boost productivity and improve quality of care. Over 72% of health care organizations are considering or have already started implementation of online, self-service applications, portals and IT systems during 2003. Over 83% of survey responding hospitals is also either considering or already started implementation of CTI, CRM, ERM, EAI and web services based enterprise tools and technology to foster KMS.

PROBLEMS OF CURRENT KMS RESEARCH

Currently, KMS researchers focus on statistical analysis of qualitative data and figuring out the relationships between different indicators. The biggest drawbacks of this approach are:

1. KMS indicators normally contain both qualitative data (survey data) and quantitative data (financial or operational data). But most of current KMS researches only focus on survey data, and hardly include quantitative data. So, it causes the research results to only partially reflect the characteristics of KMS;
2. The measurement constructs are often inconsistent and also conflicting hence there is no effective way to comprehensively assess and rank different units based on the multi-layered criteria.
3. Survey data often scatters around a certain range so averaging the data can lose information.

A Multiple Criteria Decision Making (MCDM) tool can be used in KMS research to resolve the problems in assessment under conflicting, uncertain and hierarchical conditions. Moreover, measurements of many KMS indicators contain a lot of uncertainties, which cannot be represented by crisp format, and lend themselves well to the use of fuzzy logic.

FUZZY COMPOSITE PROGRAMMING MODEL

Fuzzy Composite Index

FCP is one of MCDM techniques, which can handle mixed indicator data (quantitative and qualitative), and also work with conflicting, uncertain and hierarchical criteria. FCP methodology was developed by Bardossy and Duckstein (1992). There have been a lot of successful applications of FCP in the literature (Lee et al. 1992; Hagemeister et al. 1996; Prodanovic and Simonovic 2002; Sadip et al. 2002)

The normalization is done by using the best and worst basic indicator values that are described by the following equation (Lee et al. 1992):

$$\beta_{ij} = \frac{f_{ij} - f_{ij}^-}{f_{ij}^+ - f_{ij}^-} \text{ (When } f_{ij}^+ \text{ is best)}$$

Or

$$\beta_{ij} = \frac{f_{ij}^+ - f_{ij}}{f_{ij}^+ - f_{ij}^-} \text{ (When } f_{ij}^- \text{ is best)}$$

FCP is based on a Fuzzy Composite Index (FCI). The equation is:

$$L_j = \{\sum_{i=1}^{n_j} w_{ij} \beta_{ij}^{p_j}\}^{1/p_j} \quad (1)$$

Where, Lj is Fuzzy Composite Index for the B+1 level group j of B level indicators;
w_{ij} is weight of B level indicators in group j;
p_j is balancing factors among indicators for group j;
f_{ij}^+ is the best value of i^{th} fuzzy indicators for group j;
f_{ij}^- is the worst value of i^{th} fuzzy indicators for group j;
f_{ij} is the value of i^{th} fuzzy indicators for group j.

The final fuzzy composite index, which is used for ranking, is obtained by calculating the FCI from basic level to top level.

The weight parameters for indicators at different levels (w_{ij}) are established based on the degree of importance that users feel each indicator has relative to other indicators of the same group (Bardossy and Duckstein, 1992).

The balancing factors (p_j) reflect the importance of maximal deviations between indicators in the same group, and determine the degree of substitution between indicators of the same group. Low balancing factors (equal to 1) are used for a high level of allowable substitution. High balancing factors (equal to 3) are used for minimal substitution (Bardossy and Duckstein, 1992)

The best value (f_{ij}^+) stands for the maximum possible value of the indicator, and the worst value (f_{ij}^-) stands for the minimum possible value of indicator.

Most Likely Interval (MLI) and Largest Likely Interval (LLI)

MLI reflects the most likely range for indicator value, and LLI reflects the largest possible range for indicator value. MLI consists of both low bound (LMLI) and high bound (HMLI). LLI consists of both low bound (LLLI) and high bound (HLLI). Low bound and high bound can be same. Hagemeister et al. (1996) gives such an example: water volume has the low bound of 310,000 m^3 for LLLI, the high bound of 410,000 m^3 for HLLI, and 340,000 m^3 for both LMLI and HMLI.

Normally, there is such relationship among those values:

LLLI ≤ LMLI ≤ HMLI ≤ HLLI

In the Figure 1, the range from 4 to 6 is called Most Likely Interval, and the range from 2 to 8 is called Largest Likely Interval. LLLI = 2, LMLI = 4, HMLI = 6, HLLI = 8.

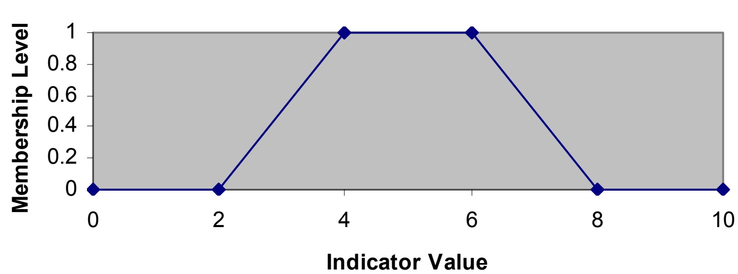

Figure 1. Trapezoidal Membership Function of a Fuzzy Number

Ideal Point and Worst Point of FCP

The normalized Ideal Point of FCP is located where all indexes are 1, and the normalized Worst Point of FCP is located where all indexes are 0. The real scenarios scatter inside those boundaries. The closer the values are to the Ideal Point, the better the scenario is.

FCP Computation Steps

Based on Bardossy and Duckstein (1992), FCP computation is divided into the following steps:

First step, utilize formula (1) to compute the fuzzy composite index (FCI) for low bound and high bound for both Most Likely Interval (MLI) and Largest Likely Interval (LLI) for each scenario. Second step, based on the computed fuzzy composite index of LMLI, HMLI, LLLI and HLLI at step 1, compute final fuzzy composite index for each scenario.

$$FCI_i = \frac{1}{2}\left(\frac{FCI(HLLI_i) - \min}{(\max - \min) + (FCI(HLLI_i) - FCI(HMLI_i))} - \frac{\max - FCI(LLLI_i)}{(\max - \min) + (FCI(LMLI_i) - FCI(LLLI_i))} + 1\right)$$

Where, i is scenario number;

$\min = \min_j(FCI(LLLI_j))$, Which is minimum LLLI in all scenarios;

$\max = \min_j(FCI(HLLI_j))$, Which is maximum HLLI in all scenarios.

Third step, compare the final FCI for all scenarios.

The ranking rule is: the larger the final FCI value, the better the scenario.

FuzzyDeciMaker

The FuzzyDeciMaker tool was developed by the Civil Engineering Department of the University of Nebraska at Lincoln. It is a software tool to implement FCP functions, which supports building tree data structure, inputting data, calculating the Fuzzy Composite Index for different levels and ranking different scenarios. It is implemented in Visual Basic and the backend data storage for data structures and scenarios is Microsoft Access.

KNOWLEDGE MANAGEMENT IN HEALTH CARE ORGANIZATIONS

The focus of this research is on the knowledge management processes in the clinical nursing function in a round-the-clock healthcare organization. While, the diagnosis and prescription of the patient's conditions and ailments fall under the physician's practice and responsibility; it is the nurse that has the majority of the contact with the patient during the patient's stay in the hospital. Therefore, the interactions between the nurse and the patient are extremely important knowledge acquisition, creation and integration events. These interactions often result in the nurse identifying new symptoms, changed conditions and critical issues. This knowledge is then used by the nurse in clinical interactions with other practitioners involved with the patient's care.

Healthcare maps closely into the newer KM process model advocated by Fischer and Ostwald (2001), which supports the paradigm of emphasis on knowledge creation. In this model the knowledge integration function is an ongoing process and is open and dynamic, where the goal is to encourage opportunities for new learning, knowledge creation and innovation. This differs from the traditional KM process model, which relies heavily on planned knowledge creation, storage and reuse. The traditional model is used in call centers and technical support organizations.

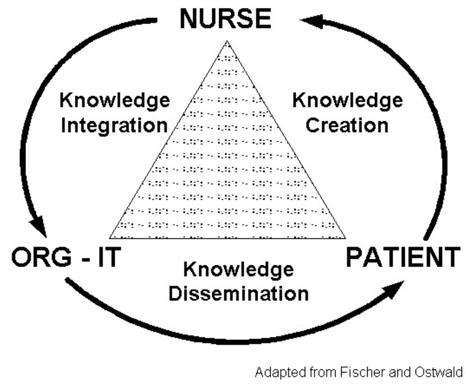

Figure 2: Knowledge Management Process in the Clinical Nursing Function

In the nursing function, the key knowledge creation transaction is between the nurse and the patient. The organization's role is to provide the IT and systems environment to achieve efficiencies by facilitating knowledge integration. Knowledge is created during the interaction between the nurse and the patient and is stored in the KMS by the nurse. The knowledge is then available to other nurses (as well as physicians and specialists) in future patient interaction scenarios (See Figure 2). The knowledge is also disseminated to patients to promote better health compliance. Personalization of this knowledge is done by the collaboration among nurses during the problem identification stage and may not always rely on the organization and it's IT.

QUALITATIVE RESEARCH MODEL

The Knowledge Management Capabilities and Organizational Effectiveness Model developed in Gold et al. (2001) captures the relationship of the key infrastructure items – technical, organizational structure and cultural capabilities and the knowledge process capabilities on organizational effectiveness. It is a validated model that has been used in different industries and does a comprehensive job of measuring the infrastructure and process capabilities that are necessary for effective knowledge management. The model also provides constructs to measure the different types of knowledge management process capabilities – acquisition, conversion, application and protection as well as constructs to measure the knowledge infrastructure capabilities of technology, structure and culture.

In addition, the constructs of Perceived Service Benefits and Risks (PSBR) from Hu et al. (2002) is added to the model to measure the extent that organizational effectiveness leads to service benefits for the patient.

Quantitative Measures

A set of quantitative measures were added to the model under the construct "Knowledge Reuse". The indicators measure the impacts of the KMS on the operational work of the nurses. Such impact may be the time to find answers to questions, percentage of time a piece of knowledge is reused, or the time saved by the use of the KM and finally the time to respond to the patient's needs. These quantitative measures also allow the ranking of the operational units in terms of their performance and help to train the fuzzy model.

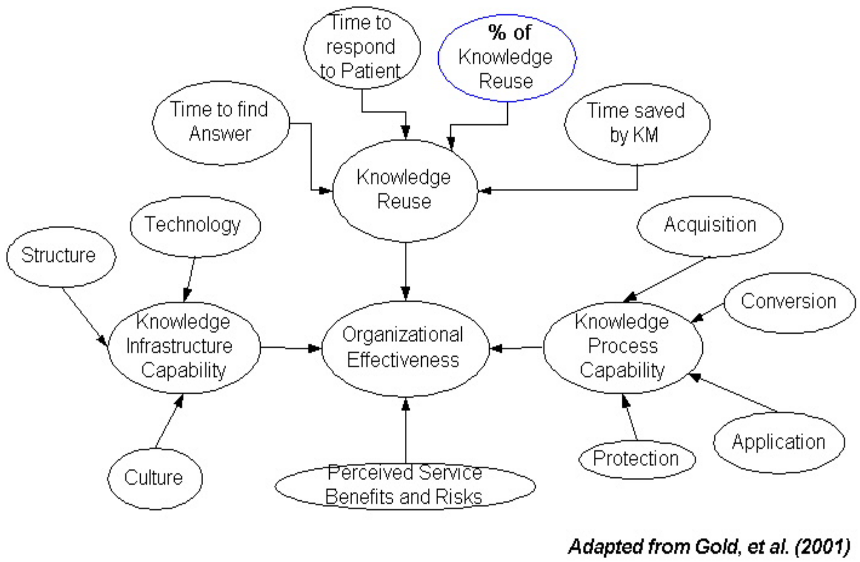

Figure 3: Research Model showing Constructs and Relationships

RESEARCH METHODOLOGY

The research methodology consists of a survey conducted in a large metropolitan area hospital. The hospital has over 300 beds, more than $350 million in annual patient revenues and has a nursing staff of over 400 nurses. Data was collected from a total of 15 nursing units.

Indicator Structure

The data collection and analysis is based on the model in Figure 3. The quantitative indicators were termed as knowledge reuse. A four level tree structure was built for Organization Effectiveness. Figure 3 only shows the hierarchy up to three levels. Each of the third level constructs (except the ones tied to knowledge reuse) has five indictors to measure each of the constructs on a 7 point Likert scale.

Perceived Service Benefits and Risks **(PSBR1-PSBR5)**	**Our organizational knowledge management:** 1. Improves the timeliness of patient care 2. Improves service productivity of nursing staff 3. Reduces unnecessary patient transfers or returns 4. Improves the overall effectiveness of patient care 5. Hinders my relationship with the patient
Knowledge Infrastructure Capability – Technology Component (TECH1- TECH5)	**My organization has:** 1. Clear rules for formulating or categorizing its clinical services knowledge. 2. Clear rules for formulating or categorizing its clinical process knowledge 3. Technology to allow collaboration with other clinical people inside the organization 4. Technology to map the location of specific types of knowledge 5. Technology to retrieve and use knowledge about its services or processes
Organizational Effectiveness **(OE1 – OE5)**	**In the past 2 years, my organization has improved its ability to:** 1. Identify new clinical service opportunities 2. Anticipate potential opportunities for new clinical services. 3. Adapt quickly to unanticipated changes 4. React to new information about the patient 5. Be responsive to new patient demands
Knowledge Infrastructure Capability – Structure (STRUC1- STRUC5)	**In my organization:** 1. Structure of departments and units inhibits interaction and sharing of knowledge 2. Structure promotes collective rather than individualistic behavior 3. Designs processes to facilitate knowledge exchange across functional boundaries. 4. Encourages employees to go where they need to for knowledge regardless of structure. 5. Structure facilitates the creation of new knowledge across structural boundaries
Knowledge Infrastructure Capability –	**In my organization:** 1. High levels of participation are expected in capturing and transferring knowledge

Culture Component (CUL1 – CUL5)	2. Employees are encouraged to ask others for assistance when needed 3. Employees are encouraged to discuss their work with people in other workgroups 4. The benefits of sharing knowledge outweigh the costs 5. Management clearly supports the role of knowledge in our firm's success.
Knowledge Process Capability – Knowledge Acquisition Component (ACQ1 – ACQ5)	**My organization:** 1. Has processes for acquiring knowledge about our patients 2. Has processes for generating new knowledge from existing knowledge 3. Uses feedback from projects to improve subsequent projects 4. Has staff devoted to identifying best practices 5. Has processes for exchanging knowledge between individuals.
Knowledge Process Capability – Knowledge Conversion Component (CONV1 – CONV5)	**My organization has processes for:** 1. Converting knowledge into the design of new clinical services 2. Distributing knowledge throughout the organization 3. Integrating different sources and types of knowledge 4. Organizing knowledge 5. Replacing outdated knowledge
Knowledge Process Capability – Knowledge Application Component (APPL1 – APPL5)	**My organization:** 1. Has processes for applying knowledge learned from experience 2. Has processes for using knowledge in the development of new services 3. Has processes for using knowledge to solve new problems 4. Makes knowledge accessible to those who need it 5. Quickly links sources of knowledge in solving problems
Knowledge Process Capability – Knowledge Protection Component (PROT1 – PROT5)	**My organization has processes to:** 1. Protect knowledge from inappropriate use inside the organization 2. Protect knowledge from inappropriate use outside the organization 3. Has technology to restrict access to the sources of knowledge 4. Values and protects knowledge embedded in individuals 5. Clearly communicates the importance of protecting knowledge
Knowledge Reuse **(KR1 – KR4)**	**For an average situation:** 1. Time needed to find an answer to a question 2. Time needed to respond to a customer/patient 3. How often knowledge is reused from past bulletins (in %) 4. Time saved by the issue of a nursing best practice or bulletin

Table 1. Constructs and Measures

All 15 nursing units provided complete data sets. The contents of all the constructs in the model are listed in the following table together with the survey questions. As seen from the table, each construct has 5 instruments to measure the construct. The survey was constructed based on a subset of questions listed in Gold, et. al. (2001) and Hu, et. al. (2002).

All of the constructs were validated in their earlier study, respectively and demonstrated adequate construct validity, convergent and discriminant validity. Factor analysis with Varimax rotation was done using SPSS on the data to revalidate the instruments in this problem domain of clinical nursing. The results from SPSS indicates that there are nine distinct components (corresponding to the nine qualitative measures) in the data with Eigenvalues greater than 1.0. However, these results are not pertinent to this study (which focuses on analysis using FCP) and hence are left out of this paper.

Project Considerations for Using FuzzyDeciMaker

Balancing Factors

Since substitution is allowed for all indicators therefore, the balancing factors for all indicators are set to 1.

Selection for Most Likely Interval (MLI) and Largest Likely Interval (LLI)

LMLI, HMLI, LLLI and HLLI are explained at section 5.2.

The values for all the qualitative survey data range from 1 (the worst score) to 7 (the best score). For dataset of each scenario, we choose the maximum value of dataset as HLLI, the minimum value of dataset as LLLI, and the average value as LMLI and HMLI.

For "Knowledge Reuse" data, i.e., the quantitative data, table 2 presents the worst value and the best score. LLLI, LMLI, HMLI, and HLLI are also determined based on different nursing units' actual situation.

Weight for Basic Indicators

Doctors and nurses were consulted about the relative weights in interviews. In the interviews, questions about the relative weights for technology, structure and culture under knowledge infrastructure capabilities were asked. The normalized weights for all the indicators given by the experts are shown in Table 2.

Indicator	PSBR1~ PSBR5	TECH1~ TECH5	CUL1~ CUL5	STRUC1 ~ STRUC5	PROT1~ PROT5	ACQ1~ ACQ5	APPL1~ APPL5	CONV1~ CONV5
Weight	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Best Value	7	7	7	7	7	7	7	7
Worst Value	1	1	1	1	1	1	1	1

Indicator	Response Time	KMS Usage Frequency	Time Saved from KMS	Time for Find Answer to Question
Weight	0.25	0.25	0.25	0.25
Best Value	0	100	100	0
Worst Value	50	0	0	40

Indicator	Technology	Structure	Culture	Acquisition	Conversion	Application	Protection
Weight	0.27	0.32	0.41	0.31	0.33	0.22	0.14

Indicator	KIC	KPC	Reuse	PSBR
Weight	0.25	0.25	0.25	0.25

Table 2. Weights, Best Value and Worst Value for Indicators

RESEARCH RESULTS AND ANALYSIS

Assessment Results for All 15 Nursing units

The ranking, final FCI, FCI for Most Likely and FCP for Largest Likely are shown at Table 3.

Nursing unit No.	13	12	4	14	15
FCP Index	0.6369	0.6197	0.6068	0.6061	0.6049
Most Likely	0.6944	0.6608	0.6775	0.6311	0.6136
Largest Likely	0.3430~0.9671	0.3629~0.9182	0.2353~0.936	0.3488~0.9481	0.3931~0.8333
Rank	1	2	3	4	5

Nursing unit No.	10	6	1	11	7
FCP Index	0.6033	0.5917	0.5714	0.5703	0.5687
Most Likely	0.6732	0.6415	0.6109	0.5840	0.5941
Largest Likely	0.2150~1	0.2590~0.9186	0.2433~0.8908	0.3167~0.8333	0.2699~0.8982
Rank	6	7	8	9	10

Nursing unit No.	5	2	3	9	8
FCP Index	0.5547	0.5518	0.5307	0.5289	0.5264
Most Likely	0.5901	0.5858	0.5274	0.5378	0.5334
Largest Likely	0.1597~0.9421	0.1655~0.927	0.2048~0.9287	0.1520~0.937	0.1765~0.9049
Rank	11	12	13	14	15

Table 3. FuzzyDeciMaker Assessment Results for All 15 Nursing units (Final)

From Table 3, we can see the comprehensive assessment results of organization effectiveness for all 15 Nursing units. There are such findings:

1. Among these 15 Nursing units, 13 have the most effective organization for KMS, and 8 has the least effective organization for KMS.
2. FCI for Largest Likely has a big value range, which shows that the original data set has a wide range and strong degree of fuzziness. It is therefore very hard to just use mean value to assess the organization effectiveness for nursing units. This justifies the use of the fuzzy model approach.

Analysis of Second and Third Level Indicators

Now, we need to investigate what indicators contribute most to the rankings. FuzzyDeciMaker offers the GUI display for FCI and ranking of different levels of indicators. Based on the results of the FCI and ranking of the second and third level indicators, we generated the following Tables 4 and 5.

Nursing unit No.	Perceived		Reuse		Infrastructure		Process		Final Rank (Effectiveness)
	FCI	Rank	FCI	Rank	FCI	Rank	FCI	Rank	
13	0.6157	**4**	0.6996	**6**	0.5783	**2**	0.6595	**1**	**1**
12	0.6264	**2**	0.6741	**9**	0.5708	**4**	0.6098	**4**	**2**
4	0.5328	**7**	0.7617	**2**	0.5702	**5**	0.5765	**6**	**3**
14	0.6205	**3**	0.6049	**11**	0.5835	**1**	0.6186	**3**	**4**
15	0.6316	**1**	0.5655	**15**	0.5758	**3**	0.6534	**2**	**5**
10	0.5126	**9**	0.7957	**1**	0.5569	**8**	0.5706	**7**	**6**
6	0.5484	**6**	0.7331	**3**	0.5469	**9**	0.5487	**8**	**7**
1	0.4930	**13**	0.7077	**5**	0.5695	**6**	0.5262	**11**	**8**
11	0.5503	**5**	0.5762	**14**	0.5694	**7**	0.5891	**5**	**9**
7	0.5111	**10**	0.6935	**7**	0.5314	**11**	0.5454	**9**	**10**
5	0.4922	**14**	0.6771	**8**	0.5238	**13**	0.5435	**10**	**11**
2	0.4955	**12**	0.7196	**4**	0.5182	**14**	0.4922	**13**	**12**
3	0.5223	**8**	0.5827	**13**	0.5265	**12**	0.5031	**12**	**13**
9	0.5104	**11**	0.6008	**12**	0.5373	**10**	0.4861	**15**	**14**
8	0.4767	**15**	0.6492	**10**	0.5080	**15**	0.4820	**14**	**15**

Table 4. Assessment Results for All 15 Nursing units (Second Level for Effectiveness)

Nursing unit No.	Acquisition	Application	Protection	Conversion	Process	Effectiveness
13	**1**	**1**	**1**	**2**	**1**	**1**
12	**6**	**4**	**6**	**5**	**4**	**2**
4	**9**	**6**	**14**	**4**	**6**	**3**
14	**2**	**3**	**5**	**3**	**3**	**4**
15	**5**	**2**	**2**	**1**	**2**	**5**
10	**4**	**8**	**12**	**7**	**7**	**6**
6	**10**	**7**	**7**	**8**	**8**	**7**
1	**12**	**9**	**4**	**14**	**11**	**8**
11	**8**	**5**	**3**	**6**	**5**	**9**
7	**7**	**10**	**9**	**9**	**9**	**10**
5	**3**	**12**	**10**	**10**	**10**	**11**
2	**14**	**13**	**11**	**13**	**13**	**12**
3	**13**	**11**	**15**	**11**	**12**	**13**
9	**15**	**15**	**8**	**12**	**15**	**14**
8	**11**	**14**	**13**	**15**	**14**	**15**

Table 5. Assessment Results for All 15 Nursing units (Third Level for Process)

From Table 4 and 5, we can see that:

1. The final ranking based on Organization Effectiveness is close to that based on Knowledge Process Capability. For example, for Nursing unit 1, both Knowledge Process Capability and Organization Effectiveness rank it as the best scenario. For Nursing unit 15, both Knowledge Process Capability and Organization Effectiveness rank it as the second worst scenario, and Organization Effectiveness ranks it as the worst scenario. So, Knowledge Process Capability plays the most important role on assessing Organization Effectiveness in the fuzzy model;
2. Other second level indicators (Perceived Services Benefits and Risk, Knowledge Reuse and Knowledge Infrastructure Capability) have less impact on Organization Effectiveness. For example, for Nursing unit 10, Knowledge Reuse ranks it as the best scenario, but Organization Effectiveness ranks it as the 6th. For Nursing unit 2, Knowledge Reuse ranks it as the best scenario, but Organization Effectiveness ranks it as the 12th;
3. Under Knowledge Process Capability, The ranking based on Knowledge Process Capability is close to that based on the Application indicator. So, Application plays the most important role in assessing Knowledge Process Capability and Organization Effectiveness.
4. Conclusion (1) fits Ghosh and Scott (2004), which states that "Knowledge Process Capability will affect Organizational Effectiveness more in a Health Care organization". Conclusion (3) fits Ghosh and Scott (2004), which state that "Application will contribute more to Knowledge Process Capability in a Health Care organization". Both of these outcomes prove the correctness of using FCP to assess KMS Organizational Effectiveness in health care organizations.

CONCLUSIONS

Based on this research study, we can conclude:

1. Fuzzy Composite Programming (FCP) can work well with mixed indicator data (quantitative and qualitative), as well as with conflicting, uncertain and hierarchical criteria;
2. FuzzyDeciMaker is a powerful and easy-to-use FCP software, which can help build and represent hierarchical indicator structures. It has capabilities to support data entry and graphical display of results.
3. Knowledge Process Capability played the most important role in assessing Organization Effectiveness of KM. Other second level indicators (Perceived Services Benefits and Risk, Knowledge Reuse and Knowledge Infrastructure Capability) have less impact on Organization Effectiveness.
4. Knowledge application process plays the most important role on assessing Knowledge Process Capability and Organization Effectiveness.
5. Among these 15 nursing units, nursing unit 13 has the most effective organization for KMS, and Nursing unit 8 has the least effective organization for KMS.

FUTURE RESEARCH

This research has demonstrated the benefits of using fuzzy logic to assess knowledge management and its impacts on organizational effectiveness. The fuzzy model is capable of working with qualitative and quantitative data, which are vague and conflicting. The data was collected from one hospital and as part of ongoing work, the study can be extended to use data from other hospitals to validate the model and results further. A more detailed analysis is being done on the nursing units to understand qualitatively the processes that they have adopted in each unit to understand in detail the rankings obtained from the model. Clearly unit 13 has applied best in class processes among the surveyed unit and details of such processes could help other healthcare organizations as they establish KM processes to manage the information overload.

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