International Journal of Mechatronics, Electrical and Computer Technology (IJMEC)
ISSN: 2305-0543 (Online), ISSN: 2411-6173 (Print)
Vol. 12 (46), Oct. 2022, pp. 5284-5292

Fuzzy knowledge management advisor system based on computing with words technique

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***Abstract*— Today, appropriate management of intellectual capital is one of the most important concerns of successful organizations. Organizations need to identify and manage their intellectual capital in order to gain sustainable competitive advantage. Knowledge Management (KM) means doing whatever is necessary to get more utilization of knowledge resources. One of the important parts of implementing KM is proper recognition of suitable solutions according to organization's properties and conditions. Our approach is based on Fernandez and Sabherwal contingency theory for identifying KM processes and solutions. It is difficult to quantitatively evaluate contingency factors affecting KM processes as such factors involve human perceptual interpretation with certain subjectively, uncertainty and imprecision. In this paper, we introduce a fuzzy method to find out the best solution for KM development based on computing with words technique. After collecting information from 101 employees of different companies, we achieved the FOU (Footprint Of Uncertainty) for 32 prefix or suffix of words that people used to describe factors and used them to establish the codebook; since human beings understand and express themselves naturally using 'words'. The encoder transforms linguistic perceptions into interval type-2 fuzzy sets (IT2 FSs) that activate engine. We used linguistic weighted average in fuzzy inference engine for aggregation of the evaluation of different aspects and then, Karnik & Mendel and Jaccard similarity algorithm is used to produce the results. In this method, the distinction between different ideas are made with more accuracy by using linguistic variables. It overcomes the problems of modeling uncertainty during computing with words by using FOUs. The decoder maps the output of engine back into a word. The output of our model could be descriptive, comparative or multilevel in case of the maturity model. An empirical study is performed to demonstrate the implementation process. This study shows people have better understanding of method when they use their own words and the result is more accurate model of their thinking. The result of this paper is a fuzzy perceptual computer that overcomes ambiguities and all problems deal with use of a limited number of options based on Likert scale to linguistic term.**

Keywords— Knowledge management, Contingency theory, Computing with words, Perceptual computing, Perceptual computer, Fuzzy logic.

I. INTRODUCTION

In the present age of information and Knowledge-based economy, where information advances at a brisk pace, the significance of knowledge is rising as one of the most influential organizational resources. Knowledge management is the systematic management of knowledge and the further process of discovery, acquisition, sharing and deployment of knowledge in organization bodies. Knowledge discovery is identifying knowledge through information and data, or deriving from extant knowledge. Knowledge acquiring defines as emphasizing the learning from within or outside of the organization. Sharing of knowledge is to effectively transfer knowledge between individuals and groups; and finally, deployment is the process of applying proper knowledge in actions and decisions [1]. Each of these deeds positively leads the organization to prosper in growth and excellence. Thus, knowledge management relies on four main kinds of KM processes. These four KM processes are supported by a set of seven KM subprocesses, as shown in Figure 1.

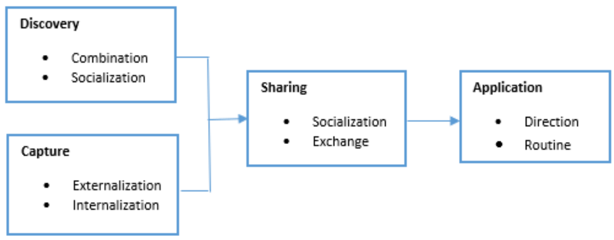

Figure 1: Knowledge Management Processes [1]

Knowledge discovery defined as extraction of new knowledge from data and information or prior knowledge. New explicit knowledge is discovered by the process of recombining and reanalysis existing explicit knowledge, data and information, while new tacit knowledge is discovered through joint activities and communications, called socialization. The knowledge capture process is achievable through two KM subprocesses externalization and internalization. Externalization and internalization help capture the tacit and explicit knowledge [2]. Sharing of Knowledge sharing is the process through which knowledge is transferred across individuals [3]. Depending on the type of knowledge is being shared, exchange or socialization

Article History:
Received Date: May. 03, 2022, Accepted Date: Jul. 06, 2022, Available Online: Oct. 01, 2022

processes are used. Knowledge application is the process of applying knowledge in decisions and actions. Direction include instructions or decisions and not the knowledge required to make them, but Routines include knowledge embedded in organizational processes that could be used as guideline for future behavior [1].

We recommend the use of an approach based on contingency theory for identifying KM processes and solutions. We want to modify what kind of a KM solution is suitable for an organization. It depends on circumstances within the organization and effective factors. We have to identify the KM solution that would be most beneficial for those circumstances. Several contingency factors influence the choice of KM processes [1]. Table 1 summarizes these categories of contingency factors affecting KM processes.

As it shown in the table, we need to use linguistic variables to describe Circumstance's factors. Linguistic variable means a variable whose values are words or expressions in a language that we used to describe another changing variable [4].

Fernandez and Sabherwal [1] proposed a method to find out appropriate KM processes based on contingency factors for identifying KM processes and solutions. This method has been of questionnaire ones which deals with the use of a limited number of options based on Likert scale. One of the problems in using the limited Likert scale is the lack of suitable conditions under which different ideas have to be expressed. In a given situation, the participants have to either agree, or disagree with a subject, or to have an indifferent answer. However, it is clear in relative judgment, people use different words to express their own opinion. Some of the questioned subjects may possibly or relatively exist within an organization. Therefore, we have to provide the possibility to express different ideas among these criteria for answerers. In this regard, different words can be used in the proposed method to cover a vast area of ideas. Words are chosen on the basis of individual's ideas from varying cultures and/or organization. There is no doubt that communication, comprehension and register of each word is much easier for them. Thereafter, in order to use words in next steps, even the model of each word is made up based on the idea given by individuals, mental model for each word can be said to raise. Also in this method, the distinction between different ideas are made with more accuracy.

Regularly, evaluation-related actions have always been connected with uncertainty and doubt in estimating quantitative or qualitative attributes. Particularly in social judgments, the perception of individuals in decision-making situation is always dependent on various attitudes, conditions and individuals [5] since different words imply different meanings for different people [6]. Hence, using numbers for an accurate and complete description of human observations is insufficient. Applying fuzzy logic in such studies is recommended [6]. One of the strategies for using fuzzy logic in evaluation is perceptual computing. The perceptual computer using analytical algorithms that allows individuals to comment by their selected words and vocabulary. Accordingly, it is favored to use perceptual computing methods when the evaluation is based on linguistic information, since the method itself is a particular form of computation with words [7]. In this method, a better cognitive model will be created for people's perceptions. This method will lead to obtaining results that are more reliable.

In this paper, we use a perceptual computer to solve the problem of qualitative evaluation using linguistic variables. We improve the user partnership in evaluation process by giving freedom to express their feeling by their own words. Real life application domains, frequently involve elicitation of information in linguistic form, since human beings understand and express themselves naturally using words. Sothis method could provide better conclusion while it captures the real values and made a better model of words. It overcome the problems of modeling uncertainty during computing with words by using FOU s while an interval type-2 fuzzy set is completely described by its footprint of uncertainty. By using type-2 fuzzy sets, we improved our model while type-2 fuzzy systems give more degrees of freedom for better representation of uncertainty compared to type-1 fuzzy sets. Using type-2 fuzzy set provides the capability of handling a higher level of uncertainty and provides a number of missing components that have held back successful deployment of fuzzy systems in human decision making. The proposed approach provides solution in the form of a ranking order of the solutions, based on their scores. This method not only explain important factors that affect knowledge management development but also, provides a clear step by step guideline for managers to choose proper solution for their organization and do the optimal investment on KM process to achieve the most profit. So, the proposed method:

Table 1. Appropriate Circumstances for Various KM Processes [1]

	Knwledge management processes							
Factors	**Combination**	**Socialization-Discovery**	**Socialization-Sharing**	**Exchange**	**Externalization**	**Internalization**	**Dirction**	**routine**
Task uncertainty	LOW	HIGH	HIGH	LOW	LOW	LOW	HIGH	LOW
Task interdepedency	HIGH	HIGH	HIGH	HIGH	LOW	LOW	LOW/HIGH	LOW/ HIGH
Tacit knowledge	LOW	HIGH	HIGH	LOW	HIGH	LOW	LOW/HIGH	LOW/ HIGH
Organizational size	LOW/ HIGH	LOW	LOW	HIGH	LOW/HIGH	LOW/HIGH	LOW	HIGH
Cost strategy	HIGH	HIGH	LOW/HIGH	LOW/ HIGH	LOW/HIGH	LOW/HIGH	LOW	LOW
Enviormental uncertainty	HIGH	HIGH	LOW	LOW	LOW	LOW	HIGH	HIGH

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- Use problem specific linguistic information to model individual views in qualitative evaluation to produce more accurate results.

- Use perceptual computing to increase efficiency and quality of the presence of uncertainty in expert assessments.
- Overcome the problems of modeling uncertainty during computing with words by using FOUs.

The remainder of this paper is organized as follows. Section 2 briefs about related work. Section 3 provides an overview of our proposed method. Section 4 describes the implementation and the experimental results. We conclude with an outlook to future works in Section 5.

II. Related work

So far, many articles have been presented on how to implement knowledge management and proposed solutions for developing KM in the organization. Each study has a different perspective on the subject and has used various methods.

Abukhader article [8] examined the status and potential of implementing a KM program in major service organizations. In this research, a questionnaire with specific options and weighted average of responses were used. Based on this, he has investigated the strategies for implementing knowledge management.

Miklosik et al. [9], by reviewing the systematic implementation of KM processes, examine the framework of the basic processes of knowledge management. They performed in-depth interviews with representatives of 25 ICT companies operating in the Slovak Republic and define its character and potential roots. Results of this analysis are perception of constraints of knowledge management implementation. They just explained important affecting factors and not an implementation solutions good for special organizations.

Mahmoodi et al. [10] are assessing the barriers to KM implementation based on the fuzzy process analysis network. Through an in-depth review of the literature on KM and researcher’s findings from observations and interviews with experts, the main barriers of KM implementation, were identified. Although they represent good survey of KM implementation but they don’t focus on suitable implementation solutions.

Karami et al. [11] have reviewed the implementation of knowledge management using quantitative and qualitative tools and introduce their model based on them. In this respect and to reduce the failure risk of KM projects, the paper aims to arrive at a conceptual model by identifying and prioritizing factors for guiding research into the successful implementation of knowledge management systems. This paper introduced some factors for organization to work on it.

All of these papers are just reviewed important and affecting factors and not proposed any method to distinguish suitable knowledge management implementation for your company. So we used contingency theory method in [1] that propose proper implementation for your organization based on organizational conditions and attributes. But, in this method people should scoring factors with yes or no answers. This approach has two major short coming: (1) the way people are required to provide their input is problematic because humans usually express their opinions in terms of words; and (2) it overlook the fact that different users may use different words to express their idea and words means different to different people.

According to non-quantifiable and subjective nature of affecting factors introduced in the theory, we prefer to use computing with words technique. Fortunately, fuzzy set theory offers a powerful tool to deal with concepts with uncertainty and imprecision.

On the other hand, Computing With Words (CWW) is a system of computation in which, the objects of computation are variables which take words rather than numbers, as values. The methodology of computing with words plays a particularly important role in the analysis and design of complex systems and decision processes [12]. Over the last years, CWW has been regarded as a very flexible technique for dealing with decision making problems and evaluating human perception, and many different approach for CWW have been proposed [13-17].

Molinera et al. [18] improving supervised learning classification methods using linguistic modeling methods in order to obtain a linguistic representation. Therefore, it is found that linguistic representation of the training data with just the necessary and sufficient precision can improve the reliability of the classification process.

Rodríguez [19] reviewed decision making problems to provide information about their preferences by eliciting their knowledge with different assessments. This paper provides an overview of the broadest fuzzy linguistic approaches for modelling complex linguistic preferences together some challenges that future proposals should achieve to improve complex linguistic modelling in decision making. In this paper [19], it has been attempted to use the concepts of perceptual computing using the qualitative assessment of KM processes and to measure the evaluation indicators because of the nature of the use of language phrases.

Madan [20] presented an algorithm to assessment based on the fuzzy linguistic parameters. Herrera [21] uses a computing with words methodology that allows experts to elicit linguistic evaluations and obtains final results as a linguistic representation of words. Moreover, this method presents further details for recognizing the effects of distinct opinions due to the use of type 2 fuzzy sets and higher level of doubt involved in the views. In such optional methods, individuals should answer with limited options pre-designed by the designer, so many comments will be inevitably combined into an existing option. However, by differentiating word’s meaning more accurate result of people mental model of thinking could be obtained.

In the previous methods, the output of the evaluation model is descriptive, comparative or multilevel in case of the maturity model. Nevertheless, it is possible to generate all three types of outputs together using our method based on perceived computing: the output based on the comparison, based on scoring and based on the classification; these actions are potential within the needs and objectives of the achievement evaluation.

The aims of our study is: (1) to find out and classify different words that people used to express their point of view as linguistic variables and then, model them as a codebook; (2) to synthesize factors by designing a CWW engine; and (3) to produce priority list of appropriate knowledge management solution for organizations.

III. THE PROPOSED METHOD

Quantitative or qualitative criteria can be used in evaluation methods. While quantitative criteria are determined through measurement and can be defined numerically, qualitative ones are derived from qualifications given by individuals. However, in some cases, due to ambiguity, uncertainty, and human perception-based knowledge, the common methods cannot be used. In such cases, if there is responding limitation among the existing options, some of the different ideas will be ignored and the evaluation results will not be complete and accurate. Therefore, when the evaluation is based on linguistic information, perceptual computing, which are particular word calculations, would rather be used [7].

Computing with words (CWW) was first mentioned by Zadeh [22] [23]. CWW is a methodology, in which words and propositions extracted from a natural language are the bases of calculation. Words and propositions are indicated how human beings make comparative and perceptual decisions in an uncertain and inaccurate environment [24]. By the use of this method, which can be used in different environments, the differences and difficulties in the relationship between reasoning and calculations can be overcome [25]. There are two main reasons in using CWW: first, when the proper numbers for responding are not found or when there is no access to these numbers for different reasons, and second, when we know the numbers, but using words is easier and more economical, or when we want to summarize the numbers [6]. Of course, this does not mean that computers literally use words instead of numbers in their calculations, rather the fuzzy logic provides a natural framework for individuals, through which they could interact with computers by means of words and computers could provide some words to return the results to them. Perceptual computer is a suitable structure for subjective judgments of individuals' ideas, which is able to calculate on the basis of words [26].

Figure 2 shows words converted to mathematical view map to another fuzzy sets in CWW engine and then reversed to words [26]. In this paper we used CWW based on IT2FS s [27].

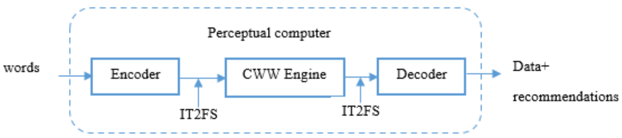

Figure 2: Specific architecture for CWW—the perceptual computer [6]

The encoder transforms words into FS s and leads to a codebook words with their associated FS models. The outputs of the encoder activate a CWW engine, whose output is one or more other FSs, which are then mapped by the decoder into a recommendation with supporting data. Therefore, the implementation of perceptual computer consists of three main steps: creating encoder, CWW engine and decoder. The overall detailed design of the perceptual computer for our system is shown in Figure 3.

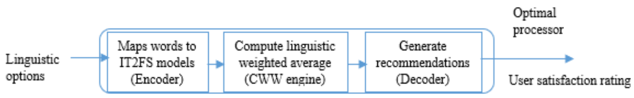

Figure 3. perceptual computer designed for our advisor system [28]

A. Encoder:

To create the proper encoder for mapping the words to the corresponding fuzzy sets, we need to create a codebook. In this codebook, IT2FS fits each word assigned until the user enters the word. The corresponding fuzzy set is produced and sent to the CWW engine for use at a later step. Creating this code set requires two steps, the first step is to take a collection of words and the latter is to consider FOUs of different words.

An IT2FS Ã is characterized by the MF $\mu_{\tilde{A}}$ (x, u), where x ϵ X and u ϵ $j_x \subseteq [0, 1]$, that is:

$$\tilde{A}: \{((x,u), \mu_{\tilde{A}}(x,u)) = 1 \mid \forall x \in X, \forall u \in j_x \subseteq [0,1]\} \quad (1)$$

where x, called the primary variable, has domain X; u ∈ [0, 1], called the secondary variable, has domain $j_x \subseteq [0,1]$ at each x ϵ X ; j_x, is called the primary membership of x, and is defined below; and, the amplitude of $\mu_{\tilde{A}}(x,u)$, called a secondary grade of Ã equals 1 for $\forall x \in X, \forall u \in j_x \subseteq [0,1]$.. Uncertainty about Ã is conveyed by the union of all its primary memberships, which is called the footprint of uncertainty (FOU) of Ã [29].

$$\tilde{A} = \left\{(x, \mu_{\tilde{A}}(x)) \middle| x \in X, \mu_{\tilde{A}}(x) = \left[\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)\right] \subseteq [0,1]\right\}$$

$$FOU(\tilde{A}) = \bigcup_{x \epsilon X} [\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)] \quad (2)$$

In Figure 4, if the continuum of triangular MFs is filled in (as implied by the shading), then the FOU is obtained. The size of an FOU is directly related to the uncertainty that is conveyed by an IT2 FS. So, an FOU with more area is more uncertain than one with less area.

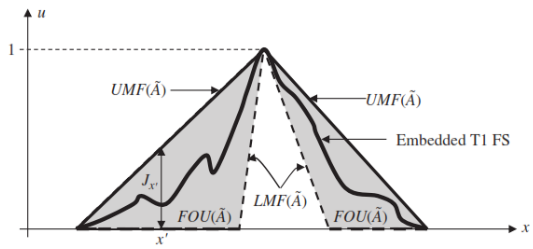

Figure 4. Interval T2 FSs and associated quantities [26]

We can present a FOU with 9 parameters and in this case IT2FS (A)̃ is shown in Figure 5 as:

$$\tilde{A} = (\bar{A}, \underline{A}) = \left((\bar{a}_1, \bar{a}_2, \bar{a}_3, \bar{a}_4), (\underline{a}_1, \underline{a}_2, \underline{a}_3, \underline{a}_4, \mathrm{h})\right) \quad (3)$$

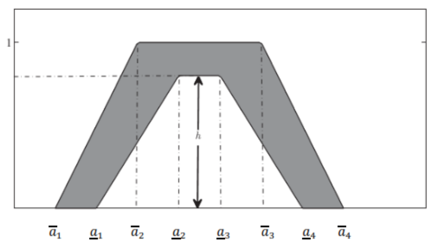

Figure 5. A 9 parameter FOU of an IT2FS

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We use these FOU in our research.

B. CWW Engine:

The central part of a perceptual computer is CWW engine which maps IT2FSs [30]. CWW engine should do needed operations on result FOUs of encoder to calculate the average and produce an IT2FS as a result. In this paper we use linguistic weighted average (LWA) in CWW engine.
At first step for computing average number of each person in the organization, we compute the result of each factors:

$$\widetilde{SGA}_{ps} = \frac{\sum_{i=1}^{n_c} \tilde{G}_{psi} \widetilde{W}_{c_i}}{\sum_{i=1}^{n_c} \widetilde{W}_{c_i}} \quad C: 1,2, \dots, n_C \tag{4}$$

Where n_c is the number of factors and $\widetilde{W}_{c_i}$ is the weight of criteria.
In next step we have to compute the whole number of organizations by aggregating all employee's questionnaires. So:

$$\widetilde{TSGA}_s = \frac{\sum_{p=1}^{n_p} \widetilde{SGA}_{ps} \widetilde{W}_p}{\sum_{p=1}^{n_p} \widetilde{W}_p} \quad p: 1,2, \dots, n_p \quad s: 1,2, \dots, n_s \tag{5}$$

Where n_p is the number of evaluators and $\widetilde{W}_p$ is the weight of him/her.

In this model we can use different weight for different people, so if you want to emphasizes persons different you can add appropriate weight for them. In this research we use the same weight for each person and criteria. Anyway, the result of CWW engine is a FOU that present the total number of organizations.

C. Decoder:

The encoder function is to produce an understandable result for final user by using FOUs that receives from the engine part. The output of a perceptual computer could be a group of words, classes or ranking [31]. Hence, the output could be a word that defines total state of the organization, a class that describes the organization's maturity level or a rank that ascertains the organization's situation among others. To producing a word or class as an output, the Decoder must compare the similarity between two IT2 FSs so that the output of the CWW engine can be mapped into its most similar word in the codebook or defined class [32] and for creating a ranking application, the decoder must rank results by a ranking method. We can use centroid as a ranking measure. KM [33] and EKM [34] algorithms can be used in order to compute centroid. By arranging result with centroid value, a ranking method is achieved.

The centroid of an IT2FS provides a measure of the uncertainty of such a FS. The centroid of IT2FS Ã is the union of the centroids of all its embedded T1 FSs [6]. So:

$$C(\tilde{A}) = \bigcup_{\forall A_e} c(A_e) = \{c_l(\tilde{A}), \dots, c_r(\tilde{A})\} \equiv [c_l(\tilde{A}), c_r(\tilde{A})] \tag{6}$$

Where:

$$c_l(\tilde{A}) = \min_{\forall A_e} c(A_e) = \min_{\forall \mu_i \in [\underline{\mu}_{\tilde{A}}(x_i), \bar{\mu}_{\tilde{A}}(x_i)]} \frac{\sum_{i=1}^{n} x_i \mu_i}{\sum_{i=1}^{n} \mu_i} \tag{7}$$

$$c_r(\tilde{A}) = \max_{\forall A_e} c(A_e) = \max_{\forall \mu_i \in [\underline{\mu}_{\tilde{A}}(x_i), \bar{\mu}_{\tilde{A}}(x_i)]} \frac{\sum_{i=1}^{n} x_i \mu_i}{\sum_{i=1}^{n} \mu_i} \tag{8}$$

Computing the centroid of FOU is one of the most important operations related to type-2 fuzzy logic system that could be very time consuming [6]. Algorithms like KM and EKM can help us to compute right and left interval values faster. Hence, we don't need to compute the centroid of all A_es.

For using ranking base on centroid method, we should compute the centroid of IT2FSs and arrange them on decreasing values [35], [36].
Also, there are many different similarity measure for computing the similarity of two IT2FS. One of the most important ones is Jaccard that defines:

$$sm_j(\tilde{A}, \tilde{B}) = \frac{\sum_{i=1}^{n} \min(\bar{\mu}_{\tilde{A}}(x_i), \bar{\mu}_{\tilde{B}}(x_i)) + \sum_{i=1}^{n} \min\left(\underline{\mu}_{\tilde{A}}(x_i), \underline{\mu}_{\tilde{B}}(x_i)\right)}{\sum_{i=1}^{n} \max(\bar{\mu}_{\tilde{A}}(x_i), \bar{\mu}_{\tilde{B}}(x_i)) + \sum_{i=1}^{n} \max\left(\underline{\mu}_{\tilde{A}}(x_i), \underline{\mu}_{\tilde{B}}(x_i)\right)} \tag{9}$$

The result of this similarity measure is a number in [0,1] where 1 shows the most similarity. If you want to have a descriptive result from your perceptual computer, then you could find the most similar word to your result in the output. So, if you want to have an output of word or group of word, you can use this method [32].

IV. Implementation and Evaluation

In this paper for mapping the words to the corresponding fuzzy sets, we need to create a codebook. In this codebook, IT2FS fits each word assigned until the user enters the word. We use IA algorithm to produce FOUs of words based on intervals. The corresponding fuzzy set is produced and sent to the CWW engine for use at a later step. By using LWA at the engine, the final results processed and result convert to understandable result with KM and Jaccard similarity algorithm.

First, we set up a codebook based on the words collected from a group of 101 employees of different company. We asked them to describe situation and factors in table 1 and collect related words that they used in descriptions. To find out the word peoples used to describe circumstances factors.

The word collections should contain the words that we would individually feel about them if we moved in through the 1 to 10 interval (assuming we scaled the scores from zero to ten) and decide which number and word correspond together.

Thus, it proceeded to collect the number of intervals between 1 and 10 for each word from 101 employees of different organizations and individuals to create an FOU for each word. The words above were randomly placed just in order to avoid any specific categorization for them in the respondent's mind, and the individual could simply express their feelings regarding the word by seeing each word.

Following this, the respondents were asked to express their feelings about each word as a number from zero to ten scale. After collecting information from a significant number of individuals, we may achieve the FOU for each word by performing a series of operations on the numerical intervals obtained for that word. In this study, the IA algorithm [37] was used to create code sets for mapping words to their corresponding FOU. The result of interval number decreases in data and FS part of IA and the FOU parameters for each word are presented in Table 2 and 3, respectively.

Table 2. The results of reducing the number of intervals during different stages of the IA

words	n	n'	m'	m''	M	m*
little	101	100	96	96	55	55
sizable	101	100	84	79	41	41
large	101	100	94	92	38	38
quite a bit	101	99	88	84	20	20
Low amount	101	100	81	71	37	31
Somewhat small	101	100	88	83	20	20
a smidgen	101	100	100	100	37	37
None to very little	101	100	98	92	23	23
humongous amount	101	100	100	93	26	26
huge amount	101	100	98	92	28	28
Very small	101	100	98	88	30	30
Vary large	101	100	100	92	18	18
Fair amount	101	100	90	85	35	35
modest amount	101	100	93	83	30	30
Very little	101	100	100	94	61	61
Moderate amount	101	100	75	69	48	48
Medium	101	100	92	78	31	31
Good amount	101	100	92	80	24	24
Extreme amount	101	100	96	92	17	17
teeny-weeny	101	100	100	92	32	32
Considerable amount	101	98	98	95	28	28
A lot	101	100	96	88	17	17
A bit	101	100	94	90	15	13
very sizeable	101	100	87	80	27	27
some to moderate	101	100	100	96	21	21
High amount	101	100	94	89	28	28
Small	101	100	94	85	24	20
Maximum amount	101	98	98	98	20	11
Some	101	100	100	96	32	28
Tiny	101	100	93	89	35	33
Very high amount	101	100	93	81	44	44
substantial amount	101	100	79	76	36	36

Given the fact that the data received from individuals accurately indicate the respondents' sense and perception associated with a particular term as a numerical interval, these intervals should be aggregated in a manner that their resultant outcome is beneficial in further calculations.

After collecting and filtering, a set of 32 suffix and prefix are modeled as shown in Figure 6. As it can be seen in these shapes, word's order is logical and explicable according to their definition and application. Obtained FOUs are different except only in bit number of words and this result shows that people have different perception for different words and different words can express distinct feeling.

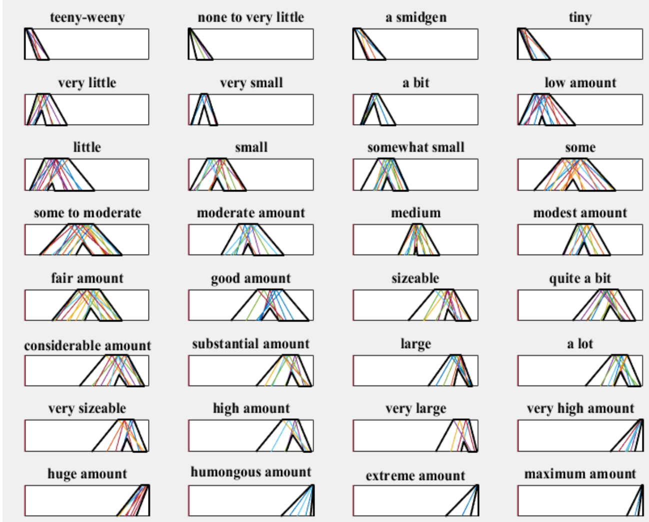

Figure 6. The 32 word FOUs ranked by their centers of centroid based on IA

Subsequently, if you want to express your measures about factors, you could use all of these words as it shown in Table 4. The perceptual computer with the described features was applied to a model dataset, in which, for each factor, a linguistic assessment is provided.

We calculate the pairwise similarity between these words and the word model of low and high in traditional method. As we expect words number 1 to 14 have lager value of similarity to low linguistic term and words number 15 to 32 have lager value of similarity to high linguistic term. But there is a significant difference between word's models that shows people have various perceptions when then use different words to express their feelings. We can map these word to their people point of view.

Therefore, as it was observed, the proposed method provides a good coverage of different ideas and creates a better mental model of individuals' viewpoints. It also makes a clearer distinction between different ideas. A summary of perceptual computer advisor is given below as Algorithm-1.

Algorithm-1: perceptual computer for advisor system

1. **Build** vocabulary of words and input their data intervals on scale 0 to 10 by surveying a group of users.
2. **Construct** FOUs of the words and store them in the form of codebook.
3. **Determine** contingency factors for your organization(Fi).
4. **For** all Fi,{Fi ∈ Fpro,∀i}
   a.Repeat
   I : Describe each factor with one of 32 specified linguistic terms.
   b.Until each term has a linguistic value.
5. **Aggregate** data values of the criteria using the LWA to generate the IT2 FSs corresponding to all.
6. **Calculate** the average centroid value.
7. **Calculate** similarities between result and proposed solutions model.
8. **Choose** the topmost similar as best solution and use 6 to rank other as a priority to do list.

Table 3. Parameters of words FOUs

Word	$\underline{a1}$	$\overline{a1}$	$\underline{a2}$	$\overline{a2}$	$\underline{a3}$	$\overline{a3}$	$\underline{a4}$	$\overline{a4}$	H
teeny-weeny	0	0	0.16	1.02	0	0	0.16	1.02	1
A smidgen	0	0	0.55	1.32	0	0	0.09	0.99	1
None to very little	0	0	0.09	1.32	0	0	0.09	1.32	1
Tiny	0	0	0.55	1.55	0	0	0.09	1.15	1
Very little	0	0	0.59	1.82	0	0	0.09	1.16	1
Very small	0.19	1	1.5	2.31	0.79	1.25	1.25	1.71	0.65
A bit	0.59	1.5	2	3.41	0.79	1.67	1.67	2.21	0.76
Low amount	0.09	1.25	2.45	4.02	1.67	1.94	1.94	2.21	0.35
Little	0.59	1.58	2.5	3.91	1.79	2.07	2.07	2.4	0.4
Small	0.09	1.5	3	4.62	1.79	2.25	2.25	2.81	0.47
Somewhat small	1.59	2.45	3.25	4.41	2.29	2.79	2.79	3.21	0.56
Some	1.59	3	4	5.41	2.59	3.5	3.5	4.41	0.65
Some moderate	1.17	4	5.5	7.83	4.09	5	5	6.41	0.65
Moderate amount	2.88	4.5	5.5	7.62	4.29	4.75	4.75	5.21	0.65
Medium	3.59	4.75	5.5	6.91	4.86	5.08	5.08	5.14	0.41
Modest amount	3.59	4.75	5.5	6.91	4.79	5.2	5.2	5.71	0.58
Fair amount	3.59	5	6	7.41	4.59	5.5	5.5	6.41	0.65
Good amount	4.59	6	7	8.41	5.79	6.5	6.5	7.21	0.65
Sizable	4.38	6.5	8	9.41	6.79	7.4	7.4	8.21	0.58
Quite a bit	5.48	7	8	9.41	6.79	7.5	7.5	8.21	0.65
substantial amount	6.09	7.5	8.75	9.81	7.79	8.21	8.21	8.81	0.49
Large	5.98	7.75	8.6	9.52	8.03	8.39	8.39	9.17	0.64
A lot	6.59	7.75	8.75	9.83	7.69	8.25	8.25	8.81	0.53
Very sizable	6.59	8	8.75	9.81	7.79	8.3	8.3	8.71	0.58
High amount	7.79	8.5	9.25	9.89	8.61	8.89	8.89	9.21	0.44
Very large	6.05	8.82	10	10	8.03	9.86	10	10	1
Very high amount	7.37	9.81	10	10	9.34	9.95	10	10	1
Huge amount	8.03	9.41	10	10	8.95	9.93	10	10	1
humongous amount	8.03	9.86	10	10	9.74	9.98	10	10	1
Extreme amount	8.68	9.91	10	10	8.68	9.91	10	10	1
Maximum amount	8.68	9.91	10	10	9.61	9.97	10	10	1
Considerable	5.38	7	8.25	9.62	7.19	7.71	7.71	8.21	0.49

Table 4. Indicators values for factors

Factors	New system	Old system
Task uncertainty	Teeny-Weeny, Smidgen, … , exterme, maximum	High or low Yes or no
Task interdepedency	Teeny-Weeny, Smidgen, … , exterme, maximum	High or low Yes or no
Tacit knowledge	Teeny-Weeny, Smidgen, … , exterme, maximum	High or low Yes or no
Organizational size	Teeny-Weeny, Smidgen, … , exterme, maximum	High or low Yes or no
Cost strategy	Teeny-Weeny, Smidgen, … , exterme, maximum	High or low Yes or no
Enviormental uncertainty	Teeny-Weeny, Smidgen, … , exterme, maximum	High or low Yes or no

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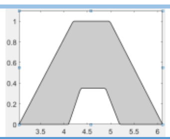
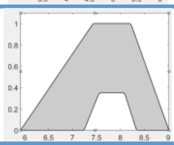
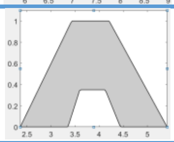
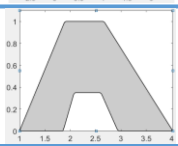
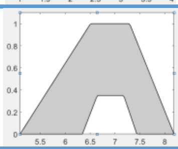
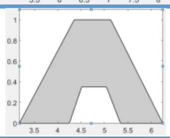
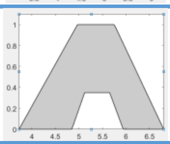
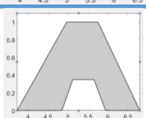
EISSN: 2305-0543, PISSN: 2411-6173

We also draw the model of solutions in Table 5 based on the ideal Circumstances for Various KM Processes described in Table 1. We apply LWA algorithm to Circumstances factor based on their response values.

By using these models, we can calculate pairwise similarity between the result and these solution models. The solution with the most similarity measure value is the best solution for our organization, so we can prioritize other solutions by this measure too. For example, an output sample for this advisor system could be a ranking like: 1.combination, 2.internalization, 3.exchange, 4.routine, 5.direction, 6.exchange and 7.socialization. It means that the most proper solution for your organization is to invest on combination and next solution is internalization and so on. This method interpreting effects on a continuum and not applying a categorical decision rule such as 'significant' or 'not significant'. By using this guideline, every organization could manage their budget to achieve optimal utilization of available resources and the most benefit form knowledge management development procedure.

Table 5. FOUs of solutions

Solution name	FOU model
Combination	
Socialization/Discovery	
Externalization	
Internalization	
Socialization/sharing	
Exchange	
Direction	
Routine	

People degree of freedom to use their own world and modeling each word based on the idea given by an individual make this method a more reliable and usable. In a simple look, it may seem that even if there are many possible answers to the questions, but these words have equal meanings. In the survey, the different ranges of using words captured from people and various words model produced by method are the reason for the denial of such attitude.

Therefore, as it was observed, the proposed method provides a good coverage of different ideas and creates a better mental model of individuals' viewpoints. It also makes a clearer distinction between different ideas by using interval type 2 fuzzy sets while this type of fuzzy sets could model not only the vagueness but also the uncertainty of different using words.

It is also worth mentioning that in the previously proposed methods applying different evaluation or valuator weighs was not possible, or if possible, numerical and approximate weighs were used. However, this possibility is easily applicable in the recently proposed method based on the different ideas of individuals, and/or as they suit the organization policies. It is possible in this method that on the basis of the importance of the individual being questioned for evaluation, a different weight is given to them to have different effects on the final result. For instance, compared with others, higher weight and importance needs to be given to the managers and experts, while they have higher awareness and knowledge regarding different issues. Taking the nature of word calculation into account, weighing words can be used to give different values, so that communication with the system and comprehension become easier for individuals. Therefore, the capability of doing weighing calculations is given to the managers of organizations by making a code book of the needed weighs.

Since the relationship between knowledge management and efficiency improvement and organizational performance is open to anyone, the development of knowledge management always has numerous advantages for organizations.

V. CONCLUTION AND FUTURE WORK

A novel knowledge management implementation approach by using linguistic variable is proposed in this paper. It takes user feedbacks in linguistic terms and processes them using the technique of perceptual computing to generate suitable recommendations. Linguistic variables were modeled by interval type 2 fuzzy sets because words can mean different things to different people. The perceptual computer has three elements: the encoder, which transforms linguistic perceptions into IT2FSs that activate a CWW engine; the decoder, which maps the output of a CWW engine back into a word; and the CWW engine. A questionnaire based method with 32 words options extracted from 100 people was used in the first step. the words are chosen on the basis of individuals' ideas from varying cultures and/or organization. The output of our model could be descriptive, comparative or multilevel in case of the maturity model. Based on our study, we believe that perceptual computing can be used to achieve improvements in the knowledge management

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EISSN: 2305-0543, PISSN: 2411-6173

implementation, while it overcomes the problems of modeling uncertainty during computing with words and produce more accurate result.

In the future, we wish to extend the evaluation criteria in selecting knowledge management solutions, so that if needed the criteria could be improved. Research is suggested in the area of criteria impact factor, so in case of finding a significant relationship between the criteria, proper weights are considered to different criteria.

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