

The Application of AI to Cultural Intelligence

Zhao Xin WU¹, Roger NKAMBOU², and Jacqueline BOURDEAU²

^{1,2}Computer Science Department, University of Quebec in Montreal, Montreal, Quebec, Canada

² LICEF, TÉLÉ-UNIVERSITÉ, Montreal, Quebec, Canada

Abstract - *In an increasingly diverse cross-cultural environment, individuals and organizations are constantly interacting with foreign cultures, which require perceptiveness and adaptability. Cultural intelligence appears as an emerging application in cross-cultural activities. Researches on this domain provide a new perspective and a promising means of intercultural conflicts and obstacles reduction. However, these researches rely mainly on questionnaires to find solutions to the cultural intelligence problems in cross-culture settings. Up until now, no research on cultural intelligence has been empirically computerized. The traditional computational techniques cannot treat cultural intelligence soft data to help individuals and organizations in solving intercultural problems. This research aims to create a new cultural intelligence model based on an innovative breed of AI technologies, and implemented in an expert system called CIES. The purpose of CIES is to support ordinary people when making culturally intelligent decisions and to improve their cultural skills when facing various authentic situations.*

Keywords: Cultural Intelligence; Soft-Computing; Expert System; Hybrid System

1 Introduction

In the context of the environment of globalization, multicultural communication and exchanges are part of today's world reality. Individuals and organizations are required to make culturally-intelligent decisions and to show their competence in culturally diverse workplaces. When confronted with cultural diversity, some individuals and organizations are able to adapt successfully to the new cultural environment, while others are not. What is the decisive factor for these opposing responses? How can good decisions be made in culturally-diverse environments? What skills can be improved to enable cultural adaptation?

In recent years, researchers have shown great interest in globalization and intercultural management. Cultural intelligence has, therefore, been presented as a new phenomenon in order to answer the above

questions. Organizational psychology and human resource management have paid great attention to cultural intelligence since its introduction. These fields of study have yielded valuable results that apply to the real cultural world. However, most current studies related to cultural intelligence do not focus on the computational aspects. Moreover, a great deal of cross-cultural knowledge is expressed as 'soft data,' such as, "this culture is more masculine", "that person is highly confident". Effectively dealing with these natural linguistic variables is beyond the scope of traditional computer technology.

The new AI technologies provide us with a means for coping with these incomplete, vague and ambiguous terms that are often used in the cultural domain. This research attempts to offer effective solutions to the problems mentioned above. These solutions mainly rely on a new computational model of cultural intelligence implemented in a system called the CIES (Cultural Intelligence Expert System). This system has integrated the cultural intelligence knowledge of experts and has the potential to achieve better performance than human experts. The CIES is considered as highly intelligent due to its wealth of knowledge, openness, scalability, flexibility, adaptability, and capability to self-learn. Such a system has three goals: 1) to assist individuals and organizations in their decision-making processes involving cultural affairs; 2) to assist people in improving their use of a specific form of intelligence based on their capacity to understand, to reason correctly, and to adapt to culturally diversified situations [1]; and 3) to facilitate the work of researchers and to better equip them in their studies of cultural intelligence.

2 Cultural Intelligence and its dimensions

In the research literature, cultural intelligence has been referred to using the acronym CQ. Researchers have different opinions regarding the concept of CQ. Earley and Ang presented CQ as a reflection of people's ability to collect and to process information, to form judgments, and to implement effective measures in order to adapt to a new cultural context [2]. Earley and Mosakowski redefined CQ as the ability of managers to deal effectively with different cultures [3]. They suggested that CQ is a complementary intelligence form,

which may explain its capacity to adapt and face diversity, as well as to operate in a new cultural setting. Peterson interpreted CQ in terms of its operation [4]. He believes the concept of CQ is compatible with the Hofstede [5] cultural values and their five main dimensions, i.e., individualism versus collectivism, masculinity versus femininity, power distance, uncertainty avoidance, and short and long term orientation. Brislin et al. defined CQ as the level of success people obtain when adapting to another culture [6]. Thomas explained CQ as the ability to interact efficiently with people who are culturally different [7] [8]. Ng et al. presented CQ as the ability to be effective in all cultures [9]. Johnson et al. defined CQ as the ability of an individual to integrate a set of knowledge, skills and personal qualities so as to work successfully with people from different cultures and countries, both at home and abroad [10].

Researchers in the field of culture also use different dimensional structures to measure CQ. Each of these researches is associated with conceptual models. These structures seek to explain the attributes that enable people to develop their abilities in various cultural contexts and, thereafter, to determine how people can improve these capabilities. Earley and Ang [2] presented the first structure of CQ which integrates the following three dimensions: cognition, motivation and behaviour. While Thomas agrees with Earley and Ang that there are three dimensions to CQ [8], he does not share their point of view regarding what these three dimensions should be. He, therefore, advocated another tridimensional structure. His belief is founded on the theory of Ting-Toomey [11], which states that the structure of CQ should be based on the skills required for intercultural communication, that is to say, knowledge, vigilance and behaviour. Vigilance acts as a bridge connecting knowledge and behaviour, which is the key to CQ. Tan [12] believes that CQ has three main components: 1) strategic thinking about culture; 2) dynamics and persistence; and 3) specific behaviours. Tan stressed the importance of behavior as being essential to CQ. If the results of the first two parts are not converted into action, CQ is meaningless. Ang and Van Dyne [1] suggested a four-dimensional CQ structure. This structure is based on the general intelligence structure of Sternberg and Detterman [13]. Ang et al. used the framework of Sternberg, which divides CQ into metacognitive CQ, cognitive CQ, motivational CQ and behavioral CQ. This structure has been widely used in the following cultural researches and studies.

3 CIES architecture

We believe that the diverse structures of CQ should be considered collectively in order to integrate the elements necessary to respond the cultural knowledge

acquired. Therefore, we build the CQ architecture. It is based on the specific CQ four-dimensional structure of Ang and Van Dyne [1]. The architecture is noteworthy because we use the four CQ dimensions as integrated and interdependent entities. It represents a comprehensive overview of the multi-aspects of the researches on CQ.

The architecture of CIES uses both the symbolic and connectionist approaches of AI. The architecture respects the cognitive concepts of Ang and Van Dyne [1] regarding the theories of global CQ, it also includes other important aspects, for example, Hofstede's theory of five cultural dimensions [5]. The architecture also relies on engineering concepts in its solutions when designing and implementing software. It offers learning mechanisms which emulate human intelligence.

In total, the architecture has an eleven-step cognitive process. It recognizes cross-cultural business-related information in natural language from its environment by using its cognitive cycle. The following describes these steps. These steps correspond to the numbers inside the rectangles in Fig.1.

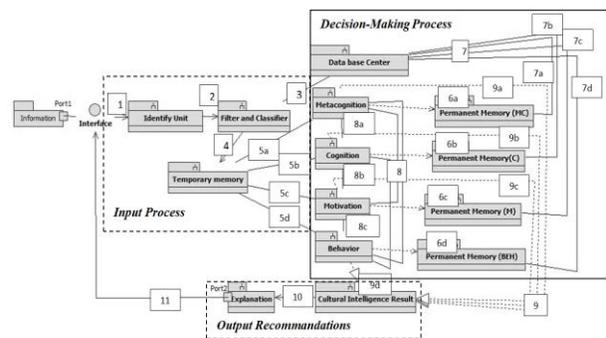


Figure 1. Architecture of CIES

Step 1: A cultural information in natural language, expressing a problem, and a question or a requirement of the user, is inputted through the user interface. This information enters the *Identify* module. This module identifies the information to determine what the user requires.

Step 2: The cultural information goes to the *Filter and Classifier* module. In this module, the information is classified and filtered from what is not useful for cultural analysis in the following steps.

Step 3: To perform this classification, the module has an associated relationship with the *Cultural Intelligence Database Center*, which has all the necessary data that the system needs, such as countries, religions, languages, and laws.

Step 4: The classified cultural data are ready to be sent to the *Temporary Memory* module. This module keeps

the data temporarily and, at the same time, interacts with the other modules.

Step 5: The *5a-Metacognitive* module, *5b-Cognitive* module, *5c-Motivational* module and *5d-Behavioral* module collect the cultural data belonging to them in the temporary memory.

Step 6: Each module depends on the consultation of its own *Permanent Memory*. These permanent memory modules are 6a for metacognition, 6b for cognition, 6c for motivation and 6d for behavior. Each permanent memory represents a complete and specific cultural database that is used by its associated module to analyze the cultural information stored in the *Temporary Memory*.

Step 7: 7a, 7b, 7c and 7d analyze the cultural information. If data are missing, permanent memories modules go to the *Cultural Intelligence Database Center* to assist in the cultural analysis of the respective modules.

Step 8: After the analysis is completed in each module, the four modules must interact with each other so that each module can adjust its cultural decision. This interaction gives a complete and effective decision before continuing to the next step.

Step 9: Following the interaction between the modules of the different CQ dimensions, the four modules in steps 9a, 9b, 9c and 9d send their final cultural decisions to the *Cultural Intelligence Result* module. In this module, the decisions of these four modules are generalized and offer significant cultural information to the user.

Step 10: The *Explanation* module justifies and explains in detail, using natural language understandable to the user, why these decisions were presented.

Step 11: The explanations are sent to the *User interface*.

4 Choices of AI techniques

CQ generally has two types of data: the first type is associated to "hard" computing; which uses numbers, or crisp values; the second type is associated with "soft" computing, which operates with uncertain, incomplete and imprecise soft data. The second type is presented in a way that reflects human thinking. When we introduce the cultural concept to cross-cultural activities, we usually use soft values represented by words rather than crisp numbers. The traditional technique, or "hard" computing, is based on Boolean logic, so it cannot treat cultural soft data. In order to enable computers to emulate humans' way of thinking and to model a human-like understanding of words in decision-making, we use a neuro-fuzzy soft-computing technique to design the CIES. This soft computing technique is capable of dealing with uncertain, imprecise and incomplete cultural soft data.

This hybrid neuro-fuzzy soft-computing technique makes use of the advantages and power of fuzzy logic and the artificial neural network (ANN). Fuzzy logic and the ANN are complementary paradigms: 1) The fuzzy logic technique is used for three reasons. First, the CQ concepts are described in natural language containing ambiguous and imprecise linguistic variables, such as "*this person has low motivation*" and "*that project is highly risky because of this religion*." Second, fuzzy logic is well-suited to modeling human decision-making processes when dealing with "soft criteria." These processes are based on common sense and may contain vague and ambiguous terms [15]. Third, fuzzy logic provides a wide range of cultural expressions that can be understood by computers. 2) ANN: Although the fuzzy logic technique has the ability and the means to understand natural language, it offers no mechanism for automatic rule acquisition and adjustment. The ANN offers learning mechanisms in an uncertain, incomplete and imprecise cultural setting, which emulates human intelligence. It presents viable solutions for processing incomplete and imprecise cultural information. The ANN can manage the new cultural data input and the generalization of acquired knowledge. The hybrid neuro-fuzzy technique represents the essence of our soft computing model.

5 Inference engine of the system

5.1 Creating fuzzy sets

All the fuzzy sets come from the CQ domain. A practical approach to form CQ fuzzy sets is used in our system. The fuzzy sets define the sets on the universe of discourse. For example, when X is the universe of discourse of metacognition, and its elements are denoted as x , the fuzzy set *Metacognition (MC)* is part of the universe X , and is defined by the function $\mu_{MC}(x)$ as a function of membership in the set *Metacognition*. This equation is expressed as: $\mu_{MC}(x): X \rightarrow [0,1]$. For every element x of universe X , the membership function $\mu_{MC}(x)$ equals the degree to which x is an element of set *Metacognition*. This degree, having a value between 0 and 1, represents the level of membership of element x to set *Metacognition*.

5.2 Linguistic variables and fuzzy rules

The idea of linguistic variables is one basis of the fuzzy set theory. A linguistic variable is a fuzzy variable. For example, when we say "the CQ is high," it means that the linguistic variable of CQ takes the linguistic value high. Thus, our cultural linguistic variables are used in fuzzy rules in the system. For example:

Rule 1:

IF Metacognition is high AND Cognition is high AND Motivation is high AND behavior is high
 THEN CQ is high

The operations of cultural fuzzy sets used in our CIES are the *Intersection* and *Union*. For example, the fuzzy operation used to create the *Intersection* of two cultural fuzzy sets A and B is as follows:

$$\mu A \cap B(x) = \min[\mu A(x), \mu B(x)] = \mu A(x) \cap \mu B(x), \text{ where } x \in X \quad (1)$$

The operation to form the fuzzy *Union* of two cultural fuzzy sets A and B is as follows:

$$\mu A \cup B(x) = \max[\mu A(x), \mu B(x)] = \mu A(x) \cup \mu B(x), \text{ where } x \in X \quad (2)$$

The CIES uses a technique called the fuzzy inference method by Mamdani [16]. Fig.2 illustrates in the CIES an example of the application of a technique called Mamdani fuzzy inference method by using triangular sets. We define that the fuzzy system as having four CQ inputs: metacognition, cognition, motivation, and behavior, and as having one output: CQ. For example, input metacognition is 7.95, cognition is 3.31, motivation is 3.41 and behavior is 2.38, inferred by six fuzzy sets rules 1,2,3,4,5 and 6; output CQ is the result from six rules 1,2,3,4,5 and 6.

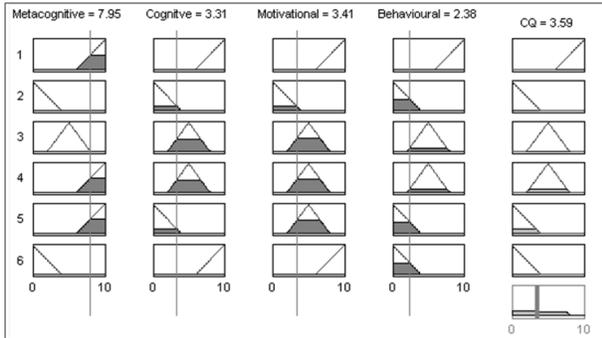


Figure 2. Example of the Fuzzy Inference System of Mamdani Using Triangular Sets in CIES

The CIES neuro-fuzzy system is similar to a multilayer neural network. Fig.3 shows the CIES neuro-fuzzy system that corresponds to the fuzzy inference model shown in Fig.2. It is represented with a neural network composed of five layers in the CIES. It has four dimensions of CQ input layer and CQ output layer, and three hidden layers that represent membership functions and CQ fuzzy rules. Each layer of the neuro-fuzzy inference model of CIES in the cross-cultural application is associated with a particular step in Mamdani fuzzy inference process. The four inputs are: metacognition (MC), cognition (C), motivation (M) and behavior (BEH), and has one output: CQ

Layer 1 - Input: No calculation is made at this layer. Each neuron corresponds to an input cultural variable. These input values are transmitted directly to the next layer.

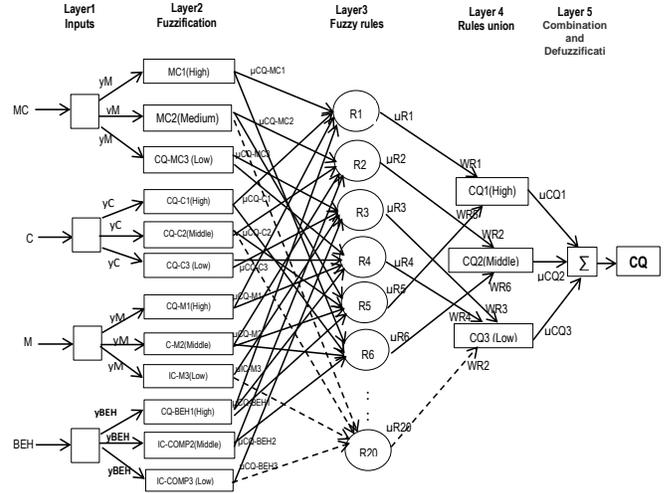


Figure 3. Soft-Computing Model of CQ

Layer 2 - Fuzzification: Each neuron corresponds to a cultural linguistic label (e.g., high, medium and low) associated with one of the input cultural variables in layer 1. In other words, the connection of the output, which represents the inclusion value, specifies the degree to which the four input cultural values belong to the neuron's fuzzy set. The connection is computed at this layer.

Layer 3 - Fuzzy Rule: The output of a neuron at level 3 is the cultural fuzzy rules. Each neuron corresponds to one cultural fuzzy rule. The cultural fuzzy rule neurons receive inputs from the layer 2 (fuzzification neurons), which represent cultural fuzzy sets. For example, neuron R1 represents cultural Rule 1 and receives input from the neurons MC1 (*Metacognition High*) and C1 (*Cognition High*). The weights (WR1 to WR20) between layers 3 and 4 are the normalized degree of confidence of the corresponding cultural fuzzy rules. These weights are adjusted when the system is trained.

Layer 4 - Rule Unions (or consequence): This neuron has two main tasks: 1) to combine the new precedent of cultural rules, and 2) to determine the output level (high, medium and low). The output level belongs to the cultural linguistic variables. For example, $\mu R1$, $\mu R5$ are the inputs of *CQ1 High*, and $\mu CQ1^{(4)}$ is the output of the neuron *CQ1 High*.

Layer 5 - Combination and Defuzzification: This neuron combines all the consequential rules and computes the crisp output after defuzzification. The composition method "sum-product" [17] is used. It computes the outputs of the membership functions defined by the weighted average of their centroids. We

apply, in this case, the triangle calculation in our neuro-fuzzy system; which is the simplest calculation of the fuzzy set as shown in Fig.4:

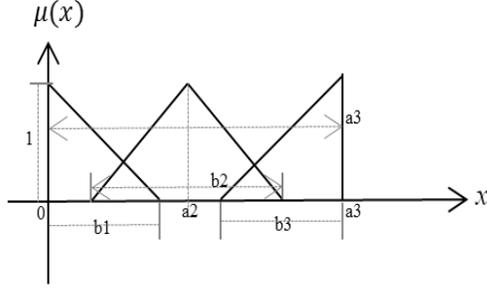


Figure 4. General Cultural Intelligence Fuzzy Sets

Where a_2 is the center and a_3 is the end of the triangle. b_1 , b_2 and b_3 are the widths of fuzzy sets which correspond with *CQ 3 (Low)*, *CQ2 (Medium)* and *CQ1 (High)*. The calculation formula of weighted average of the centroids of the clipped three CQ fuzzy sets CQ High (CQH), CQ Medium (CQM) and CQ Low (CQL) are calculated as:

$$y_{CQ} = \frac{\frac{1}{3}b_1^2\mu_{CQH} + a_2b_2\mu_{CQM} + \left(a_3 - \frac{2}{3}b_3\right)b_3\mu_{CQL}}{b_1\mu_{CQH} + b_2\mu_{CQM} + b_3\mu_{CQL}} \quad (3)$$

5.3 Supervised and unsupervised learning

The soft-computing model can easily be modified by changing, adding or subtracting CQ rules through two main types of learning occurring in the CIES neuro-fuzzy network: supervised learning and unsupervised learning. The supervised learning is the type of training where the neuro-fuzzy network is provided with desired outputs to improve its performance. We provide to the system the fully processed external CQ experts' data, required for the supervised learning. These data are processed user cases. Each user case contains the original input cultural data, and the output data provided by cultural experts, that CIES is expected to produce. The CIES compares actual output with the cultural experts' data from the training case. If the actual output is different from the data given by experts in the training case, the CIES weights are modified. The back propagation algorithm is used in the CIES. The signal difference at the output of neuron n at sequence s is calculated as showed in equation (4). We increase sequence s by one, and repeat the process until the preset difference criterion is satisfied.

$$D_n(s) = y_{e,n}(s) - y_n(s) \quad (4)$$

Where $y_{e,n}(s)$ is the cultural experts' data of neuron n at sequence s , the CQ rules for updating weights at the output layer are defined in equation (5) as:

$$W_{mn}(s+1) = W_{mn}(s) + \Delta W_{mn}(s) \quad (5)$$

$\Delta W_{mn}(s)$ represents the weight correction. We use a forward procedure method to update CQ rules' weight W_{mn} . Fig. 5 shows an example of the result where CIES trains weights from bad rules to the desired CQ rules.

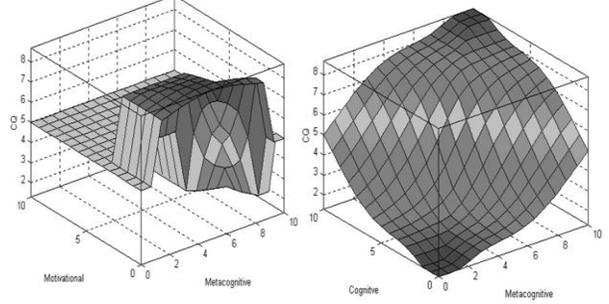


Figure 5. An Example of Supervised Learning

In contrast to supervised learning, with unsupervised learning in CIES, the neuro-fuzzy network is trained without desired output. The unsupervised learning does not require external cultural experts' data. During the learning process, the CIES receives a number of different original input user cases, find relationships in these cases and build new rules based on these cases used. The CQ rules for updating weights at the output layer are calculated in the equation (6). The equation (6) shows how the CIES changes the CQ rules weights, between a pair of neurons in the unsupervised learning process, through multiplication of input and output signals.

$$W_{mn}(s+1) = W_{mn}(s) + \alpha y_n(s)x_m(s) \quad (6)$$

$\Delta W_{mn}(s) = \alpha y_n(s)x_m(s)$ represents the weight correction by Hebbian algorithm [18] in CIES, α being the learning rate parameter.

6 Data acquisition and the application domains

Christine Kon et al. [19], Ang, Van Dyne et al. [20], and Ang et al. [1] developed a self-evaluation questionnaire with 20 items measuring CQ. This questionnaire was used to collect data for studies on the capabilities of the test subjects regarding their cultural adaptation capacity. This questionnaire is generally divided into four sections: CQ metacognitive CQ, cognitive CQ, motivational CQ and behavioral CQ. For example, one of the items is "I am conscious of the cultural knowledge I use when I interacting with people with different cultural backgrounds." Linn Van Dyne et al. [21] developed a version of the questionnaire from the point of view of an observer. It is also based on the 20 items of Ang et al. [1] which measure the CQ of individuals. The questionnaire was adapted from each

item of the self-evaluation questionnaire to reflect the assessment made by an observer rather than the trainee himself. For example, the item of the questionnaire mentioned above changes from: "I am conscious of the cultural knowledge I use when..." to "This person is conscious of cultural knowledge he / she uses when"

As explained by Linn Van Dyne et al. [21], these questionnaires also allow for the effective assessment of CQ in practical applications. Among other potential applications, we can identify three application domains covered in our system. They are *Business Activities*, *Expatriates Assignments* and *Training*. Thus, we adapted the self-evaluation questionnaire of Ang et al. [1], and the observer questionnaire by Linn Van Dyne et al. [21], in order to measure CQ for these three application domains. By collecting the data from these two questionnaires, first, the data can be prepared and be used in our neuro-fuzzy network future training. Second, the user or organisations' expatriate's assignments can be evaluated so that proper training can be offered by CIES.

7 Implementing the CIES

We would like the CIES to be capable of acquiring, extracting and analyzing the new knowledge of the cultural experts. First, it should be able to: 1) express knowledge in a form that is easily understood by the users, and 2) deal with simple requests in natural language rather than programming language. Second, the CIES should consist of an efficient team of cultural experts who are able to make decisions and provide explanations in the decision-making process in culturally diverse settings. Hence, we integrated the neuro-fuzzy soft-computing model into an expert system. It relies on the functional «consciousness» mechanism for much of its operation [14]. Its modules communicate and offer information to each other. Fig. 6 shows the system structure of the CIES. This structure includes four main modules:

1) *The CQ knowledge base* is represented by the trained neuro-fuzzy network. This module contains CQ knowledge that is useful for solving CQ problems. The soft-computing technique used in this module makes the system able to reason and learn in an uncertain, incomplete and imprecise CQ setting. It supports all the cultural decision-making steps in the system. This module connects with three different units which are *New Data*, *Training Data* and the *Cultural Intelligence Database Center*. *New Data* include users' requests for solving a given problem that involves some cultural affairs. *Training Data* are a set of training examples. They are used for training the neuro-fuzzy network during the learning phase. The *Cultural Intelligence Database Center* mostly contributes to the knowledge

gathered from data about different cultural aspects which has been collected from different countries.

2) *The Cultural Intelligence Rules* examines the CQ knowledge base and produces neuronal rules which are implicitly «buried» in the CIES network.

3) *The Inference Engine* is the core of the CIES. It controls the flow of cultural information in the system, and initiates inference reasoning from the knowledge base in the *Cultural Intelligence model*. It also concludes when the system has reached a decision.

4) *The Explanation* clarifies to the user why and how CIES achieved the specific cultural results. These explanations include analysis, advice, conclusion, and more required facts for deeper reasoning.

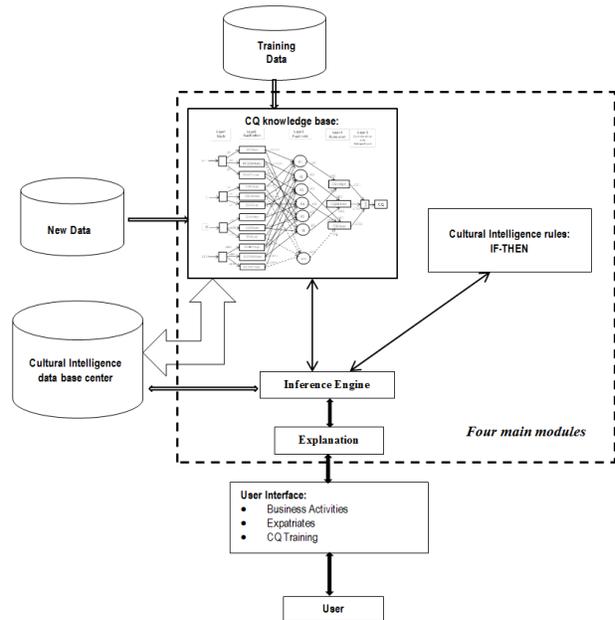


Figure 6. Structure of CIES

7.1 CIES for decisions making

The CIES possesses generic CQ, that is not specific to a particular culture (such as USA or China etc.). The system shows great capabilities of cultural adaptation by modeling the human decision-making process in situations characterized by cultural diversity. Furthermore, because of its elaborated cultural schemas and analytical abilities, the CIES can help users to identify and understand key issues in cultural judgment and decisions making, giving them the corresponding explanations.

For example, Fig.7 and Fig.8 present an output of the *Business Activity* application domain of how the CIES can help a user to make a decision, by taking into consideration his/her inputted request. The CIES prototype system follows the decision-making cycle process shown in Fig.1. The input data are specific

cross-cultural questions in the natural language of the users. The system provides two outputs as an answer to the question. Output1 (Fig.7), gives a general decision to answer the question asked by the user.

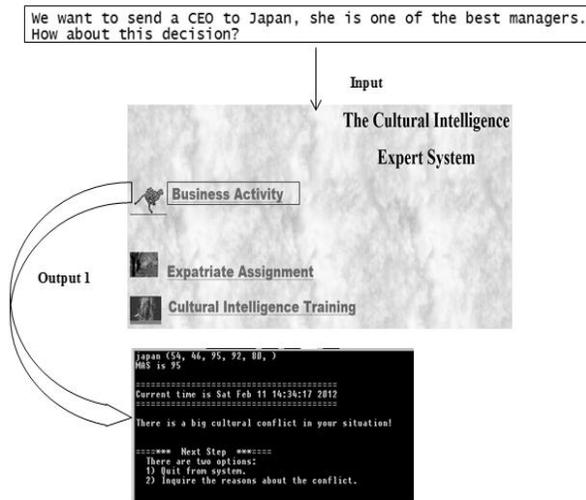


Figure 7. Business Activity in CIES Prototype (Output 1)

Output2 (Fig.8), gives more detailed explanations to clarify to the user why the system reached this decision.

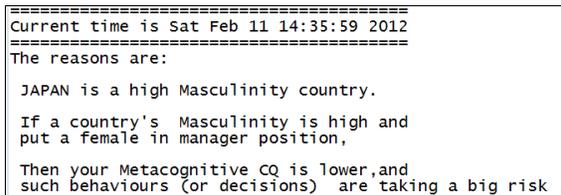


Figure 8. Business Activity in CIES Prototype (Output 2)

7.2 CIES for training

The CIES could be used in self-awareness training programs. The system provides important insights about personal capabilities and information on the user's own CQ in cultural diversity situations. Users can get two evaluations (self or observer [1] [19] [20] [21]) on the 20-itemed questionnaires so as to compare their results. Organizations could also use CIES (both self and observer evaluations) to evaluate or train, for expatriate purposes, employees who may be well-adapted. The CIES serves as an efficient team of top CQ tutors who work constantly with individuals or organizations wanting to have cross-cultural recommendations and insights on how to increase their efficiency in culturally-diverse settings. Fig.9, Fig.10 and Fig.11 present one part of the results of the self-evaluation questionnaire of a user in the CIES prototype. The CIES provides different feedback to a user receiving a high score (8>), than it does to a user receiving a low score (6<). In addition, it accordingly gives useful suggestions for

personal self-development as required. This process permits the CIES to evaluate users so as to identify their problems in the CQ domain. The CIES next offers a tailored course to users based on the results of the evaluation. Moreover, during the training course, the system uses natural language to communicate with users in order to provide them a stress-free and friendly learning environment.

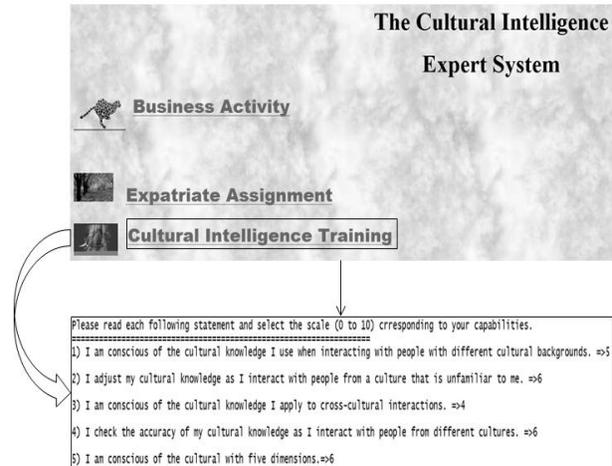


Figure 9. CIES Prototype for Training (Self-Evaluation Questionnaire)

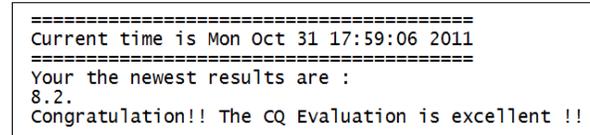


Figure 10. CIES Prototype (Output1: high score 8>)

Output 2 (Fig.11), gives useful suggestions for self-improvement to the user, when CQ is required.

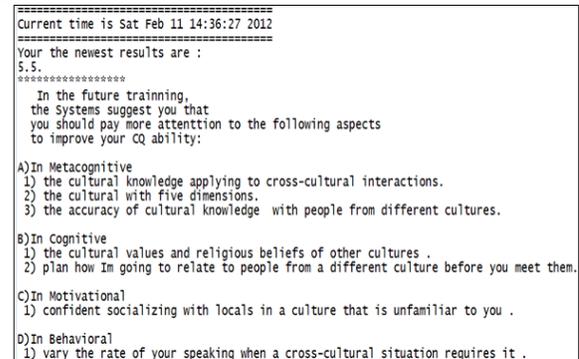


Figure 11. CIES Prototype (Output 2: low score 6<)

Three cultural experts have validated our computational CQ model, as well as that of the CIES prototype system. This validation ultimately reflects the consistency between the real world and the artificial CIES system. The CIES prototype system was tested on one hundred people. Based on the results of the validation, the cultural experts compared the CIES

results with their own. These experts concluded that the cross-cultural business decisions recommended by CIES are similar to the ones suggested by a human expert.

8 Some interesting features of CIES

First, due to the powerful designed functions and the CQ capabilities in CIES, the CIES could evaluate users and expatriates employees along with providing them specific cultural recommendations by using its knowledge to train people to improve their CQ skills, in addition, it could be used as a CQ decision-making support system to help individuals and organizations take cultural decisions in cross cultural activities. The CIES is also able to adapt dynamically to the CQ capacity of users. Second, this system is open in the sense that it can provide a standard interface that can facilitate further development. Third, the CIES is extensible, both in terms of the system concept model and the implementation of the system. Fourth, this system has the potential to work as an extended cultural and cognitive agent which could integrate into another existing intelligent system.

9 Conclusion

CQ is the human ability to capture and reason appropriately in culturally diverse settings. CQ can be measured with four dimensions. Thus, we built a CQ computational model based on a soft-computing technique so as to integrate these dimensions and embody an expert system called the CIES. This paper shows how the CIES can be used as a "culturally aware" system. The research captures the essence of culture and addresses culture from the perspective of the intelligence of an individuals or organizations wanting to develop their ability to adapt to various cultures. The CIES enables users to be more efficient and "intelligent" as they develop their cultural skills. The CIES acts as an intelligent cultural expert assistant which helps individuals or organizations to make better decisions in cross-culture activities, and it enables users to solve cultural problems that would otherwise have to be solved by cultural experts.

The contribution of our research is, first and foremost, to fill the gap between CQ and AI. Second, it improves the application of CQ theories in the field of cognition. The research focuses on modeling four CQ dimensions that are interdependent and integrated. As a result, the theories are complete, efficient, and precise in their applications. Third, we brought to the field of AI the computerization of CQ. As a result, new research topics and directions relevant to this research have arisen, and the range of computational intelligence possibilities has been expanded. Fourth, our research is groundbreaking as it simplifies the work of the researchers by freeing them from heavy, complex and

repetitive tasks, normally carried out manually in CQ studies. The algorithms and techniques used in this research may offer some enlightenment as they can be applied to other research domains to improve model designs and system performances.

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