Building a Cultural Intelligence Decision Support System with Soft-Computing

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***Abstract* - The international business and traditional business intelligence face challenges in successfully adapting to cultural diversity. This paper introduces cultural intelligence as a new perspective and a new way to alleviate these challenges. Furthermore, based on soft computing technology, this research aims to invent a cultural intelligence computational model and to implement the model in an expert system. In the cultural intelligence domain, this paper presents how this model deals with linguistic variables, soft data and human decision making with hybrid neuro-fuzzy technology, which also possesses parallel computation and the learning abilities.**

Keywords - Cultural Intelligence, Decision Making, Fuzzy Logic, Artificial Neural Network, Soft-Computing.

I. INTRODUCTION

Globalization has dramatically changed the way business is conducted. It has intensified worldwide social relations and connected workers in distant localities, making local concerns global and global concerns local. Individuals, companies and organizations have capitalized on this reality to establish centers in different countries in order to develop their international business activities. In this new reality, individuals, companies and organizations must form global strategic alliances to deal with worldwide competitors, suppliers and customers [1]. When confronted with cultural diversity, some are able to make appropriate decisions and adapt successfully to the new cultural business environment [2], while others are not. What is the decisive factor for these opposing responses? How can good decisions be made in culturally diverse business environments [3] ?

In recent years, researchers have shown a vast interest in globalization and intercultural management. Ang and Earley introduced the concept of cultural intelligence (CQ) to the social sciences and management disciplines in 2003 [4]. CQ has, therefore, been presented as a new phenomenon capable of answering the above-mentioned questions [5]. Organizational psychology and human resource management have paid a great deal of attention to CQ since its introduction. These fields of study have yielded valuable results that apply to the real business world.

However, since Earley and Ang put forward the concept of CQ in 2003, there has been no research on CQ with artificial intelligence (AI) technology with the purpose of assisting individuals, companies and organizations in making good decisions in order to function effectively in this culturally diverse environment. Indeed, most current studies pertaining to CQ do not integrate any AI technology. The current state of CQ research in AI leaves an important gap in our understanding of what individuals, companies and organizations need to function effectively in this global work environment. In addition, traditional business intelligence (BI) has encountered two challenges: the first involves determining the means of adapting to cultural diversity; the second pertains to treating cultural soft data for decision making [6]. Our claim is that when CQ is applied to individuals, companies and organizations in the fields of business, it should be computerized.

This research attempts to offer effective solutions to the aforementioned problems. It is the first attempt to invent a computational model of CQ implemented in an intelligent system to resolve cross-cultural business challenges. The main reason for inventing such a system is that, in the real business world, there are not enough qualified cultural experts to help users make better business decisions, and these experts may lose some of their effectiveness after long consecutive hours of work. Moreover, the sphere of application has been confined to cultural experts and researchers. From a user's point of view, this research offers an intelligent system that behaves like an efficient team of top cultural experts that works continuously with users. Furthermore, this system has the potential to achieve better performance results than human experts.

There are three goals behind such a system that aims to help individuals, companies and organizations cooperate more effectively with people from different cultural backgrounds: (1) to assist them in their business decision-making processes involving cultural affairs; (2) to assist them in improving their CQ capacity, which would be particularly well suited to overseas assignments [4]; and (3) to facilitate the work of researchers and to equip them with more effective tools in their studies on CQ.

This paper consists of eight sections, which is highly focused on the conceptual-theoretical background of CQ computational model and the general architecture of our system. In Section I, we state the research question and research objectives. In Section II, we briefly discuss the concepts that are applied to this research, in particular the concept of CQ and its dimensions. In this section, the relationship between business and CQ will be present. Also included is our CQ conceptual model; on the basis of this model, we create our CQ computational model. In Section III, we provide a detailed explanation of our AI technology choices applied to our computational model. Furthermore,

we introduce the theory of fuzzy and fuzzy rules that are applied to our system. In Section IV, we discuss the fundamental CQ computational model. In Section V, we demonstrate how our computational model is implemented into an expert system. We present the structure of our system and identify the main modules in the structure, and we explain how these modules work. In addition, we explain how we collect and analyze data and knowledge in the CQ domain for our system in order to make its design more explicit. In Section VI, we present an overview of the system's cognitive architecture and its cognitive processes. In Section VII, we explain the details of the evaluation of our computational model and the system. Finally, in Section VIII, we state the contributions of this research.

II. LITERATURE REVIEW AND RELATED WORK

This research draws from many different fields, each with its own richness, peculiarities and complexities. We attempt to bring the many concepts, points of views and propositions to work together. As such, the discovery of a global theory is an appropriate first step for our research and providing a clear view of what is generally understood is a necessity in this first step.

CQ is based on two basic concepts: one is *culture*, and the other is *intelligence*. In this section, we first define the concept of culture. We then explain the concept of intelligence. We present definitions of CQ and its dimensions from the different points of view of various researchers and explain the links between CQ and business.

A. Culture

According to a dictionary definition, culture is: *"the totality of socially transmitted behavior patterns, arts, beliefs, institutions, and all other products of human work and thought''* (The American Heritage Dictionary of the English language, Fourth Edition, 2000). Dictionary definitions of culture can incorporate multiple elements such as history, common traits, geographical location, language, religion, race, hunting practices, music, agriculture, art, etc.

Culture is not something that has an existence outside of the actions and experiences of the individuals who reproduce it. Culture is a context; it informs and shapes individual behavior only as it is simultaneously reproduced and reinforced by that very behavior. Cohen et al. propose a definition of culture [7]: *"Culture is an information pool that emerges when members of a community attempt to make sense of the world and each other as they struggle and collaborate with each other to get what they want and need (e.g., food, sex, power, acceptance, etc.). Because individuals construct their conceptions of the world from their own experiences and for their own motivations, their understandings vary from one another depending on the characteristics of the individuals, the nature of the domain learned, and the social situations in which learning takes place''.*

Hofstede [8] defines culture as subjective and considers national culture to be a part of a greater global culture. Hofstede [9] states that culture is a structure of collectively held values and collective mental programming, which separate or distinguish various groups of people from others. He believes that although there may be various subcultures, all nations share a national culture. Hofstede identifies the three levels in his model of collective mental programming as human nature, culture, and personality (see Fig. 1). All three levels of mental programming have an impact on how individuals react to their environment. Human nature plays a role in the development of culture over time, as well as in the development of people. An individual's culture, although it can be the same among a group of people, differs slightly with each individual, as an individual may act and behave slightly differently than others in his/her culture group due to the influence of human nature and personality. An individual's personality indirectly influences culture as it plays a role in how an individual accepts or rejects various parts of his/her culture.

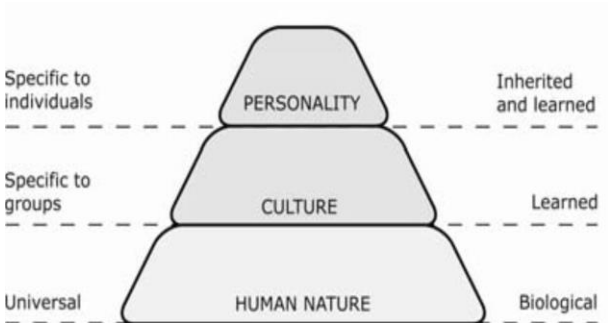


Figure 1. Three Levels of Mental Programming (Hofstede, 1980)

B. Intelligence

Early research in academic settings tended to view intelligence narrowly as *the ability to grasp concepts and reason correctly with abstractions and solve problems* [10]. Sternberg et al. [11] identified a new type of intelligence known as real-world intelligence. They declared that intelligence may be displayed in places other than the classroom and focuses on specific content domains. In our review of the literature, we found about twenty definitions of academic and 'real-world' intelligence. Although an extraordinary diversity is found within these definitions, there are striking commonalities as well. To better understand the conceptions of intelligence, we classify and summarize the domains referred to by Sternberg et al. [11] in Table 1, which covers the majority of definitions of intelligence. The framework does not capture the detail of any single definition; it shows, however, the degree to which there exists a consensus among theorists regarding the broad outlines of a definition of intelligence. Furthermore, it shows how quite diverse conceptions of intelligence all have a certain basic premise in common.

As we can see in the Table 1, theorists identify three main loci of intelligence: (1) intelligence within the individual; (2) intelligence within the environment; and (3) intelligence within the interaction between the individual and the environment. Within these three main loci, there are a number of more specific definitions of intelligence.

1) Intelligence within the Individual

Theorists identifying intelligence as existing within the individual define three main levels:

TABLE 1. OVERVIEW OF DEFINITIONS OF INTELLIGENCE (STERNBERG ET AL., 1986)

I: In individual					II: In Environment		III: Individual-environment interaction
A: Biological level	1.Across Organisms	a. Between species			A. Level of culture/society	1.Demands	
						2.values	
						3.Demands-values interaction	
		b. Within species			B. Level of niche within culture/society	1.Demands	
		c. Between-within interaction				2.Values	
	2.Within organisms	a. Structure				3.Demands-values interaction	
		b. Process					
		c. Structure-process interaction					
	3.Across-within interaction				C. Level × sublevel interaction		
B: Molar level	1.Cognitive	a. Metacognitive	i. Processes				
			ii. Knowledge				
			iii. Process-knowledge interaction				
		b. Cognition	i. Processes				
			ii. Knowledge	(a) Selective attention			
				(b) Learning			
				(c) Reasoning			
				(d) Problem solving			
				(e) Decision making			
			iii. Process-knowledge interaction				
		c. Metacognition-cognition interaction					
	2.Motiviational	a. Level (magnitude) of energy					
		b. Direction (disposition) of energy					
		c. Level-direction interaction					
C. Behavioral level	1. Academic	a. Domain General					
		b. Domain-specific					
		c. General-specific interaction					
	2. Social	a. Within- person					
		b. Between-person					
		c. Within-between person					
	3.Practical	a. Occupational					
		b. Everyday living					
		c. Occupational-everyday living interaction					

a) *Biological level*, which can be established either across or within organisms. Intelligence can be viewed within the context of the evolution of a single species and the genetics of that species, or within the interaction between the evolution of an interspecies and the genetics of that interspecies. Within organisms, intelligence can be viewed in terms of the structure of the organism, or in terms of process. Furthermore, it is possible to look at the interaction between structure and process.

b) *Molar level* emphasizes three principal aspects of mental functioning:

- *Cognitive Aspect*: This deals with three main kinds of cognition: (1) Metacognition; (2) Cognition; and (3) the interaction between Metacognition and Cognition. Metacognition refers to knowledge about and control of one's cognition. Cognition refers to what is known and controlled by metacognition. Cognitive theorists place a great deal of importance on the interaction between metacognition and cognition for individuals to function intelligently; metacognition must be modified to accommodate cognition and vice versa. Both aspects of functioning seem to be a necessity for cognitive theorists, regardless of what they are called or how they are classified.
- *Motivational Aspect*: Motivational theorists argue that there is more to intelligence than cognition and that motivation must also be taken into consideration. Three principal properties of motivation need to be considered: (1) the level of the motivation; (2) the direction of the motivation; and (3) the interaction between the level and direction of motivation. An individual may have the motivation to learn, but this motivation may not be equally directed to all kinds of learning; therefore, it is necessary to take direction into account. Intelligence is affected not only by the amount of learning, but also by the kinds of learning, and both the amount and kind of learning are affected by motivation.
- *Behavioral level*: This is an analysis of what one does rather than what one thinks about. Behavioral theorists argue that intelligence resides in one's behavior rather than in the mental functioning that gives rise to the behavior.

2) Intelligence within the Environment

Some theorists view intelligence as residing within the environment, either as a function of one's culture and society, or as a function of one's niche within the culture and society, or both. In essence, culture determines the very nature of intelligence. The culture, society or niche within the culture and society is generally a function of the demands of the environment in which people live, the values held by the people within that environment and the interaction between these demands and values.

3) Intelligence within the Interaction between the Individual and the Environment

Many theorists define intelligence as the interaction between the individual and the environment. Understanding intelligence may be facilitated by considering the interaction of people with one or more environments and by recognizing the possibility that people may be differentially intelligent in different environments, depending on the demands of these various environments.

C. Cultural Intelligence and its Dimensions

In the literature, researchers have different opinions regarding the concept of CQ. Earley and Ang [12] present CQ as a reflection of people's ability to collect and process information, to form judgments, and to implement effective measures in order to adapt to a new cultural context. They also indicate that CQ should predict performance and adjustment outcomes in multicultural situations when an individual is faced with diversity. Earley and Mosakowski [13] redefine CQ as the ability of managers to deal effectively with different cultures. They suggest that CQ is a complementary form of intelligence, which may explain the capacity to adapt to cultural diversity, as well as to operate in a new cultural setting. Peterson [14] interprets CQ in terms of its operation. He believes that the concept of CQ is compatible with the cultural values of Hofstede and their five main dimensions [15], i.e., individualism versus collectivism, masculinity versus femininity, power distance, uncertainty avoidance, and short- and long-term orientation. Brisling et al. [16] define CQ as the level of success people obtain when adapting to another culture. Thomas [17] [18] explains CQ as the ability to interact efficiently with people who are culturally diverse. Ng and Earley [19] present CQ as the ability to be effective in all cultures. Johnson et al. [20] define 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.

Researchers in this field also use different dimensional structures to measure CQ. All of this research is associated with conceptual models. These structures seek first to explain the attributes that enable people to develop their abilities in various cultural contexts, and then to determine how people can improve these capabilities. Earley and Ang [21] present the first structure of CQ, which integrates the following three dimensions: Cognition, Motivation and Behavior. While Thomas [22] agrees with this tridimensional CQ, he does not share their point of view regarding what these three dimensions should be. Therefore, he advocates another tridimensional structure. His belief is founded on the theory of Ting-Toomey [23], which states that the structure of CQ should be based on the skills required for intercultural communication, that is to say, knowledge, vigilance and behavior. Vigilance acts as a bridge connecting knowledge and behavior, which is the key to CQ. Tan [2] believes that CQ has three main components: (1) strategic thinking about culture; (2) dynamics and persistence; and (3) specific behaviors. Tan stresses the importance of behavior as being essential to CQ. If the first two parts are not converted into action, CQ is meaningless. Ang et al. [6] subsequently suggest a multifactor construct based on Sternberg and Detterman's framework of general intelligence [11]. CQ similarly focuses on a specific domain-intercultural setting of intelligence, and is motivated by the practical reality of globalization in the business workplace [12]. They divide CQ into metacognitive CQ, cognitive CQ, motivational CQ and behavioral CQ. This structure has been widely used in the following cultural research and studies. Here, we give more details of the role of each of the four CQ dimensions from their work:

1) *Metacognitive CQ* is the critical dimension that enables users to move beyond cultural stereotypes and to know when and how to apply their cultural knowledge. Individuals with a high metacognitive CQ are aware of unique individual characteristics, such as diversity within cultures and the influence that context has on behavior. They know when to suspend judgment and when to look for additional cues. Consequently, they engage in more appropriate behaviors in different intercultural situations.

2) *Cognitive CQ* emphasizes the knowledge of cultural values and orientations, as well as the knowledge of cultural universals such as the legal, political, economic and social systems of different cultures. This knowledge provides a useful starting point for users in their interactions with others. Users with a high cognitive CQ understand key issues and differences in behaviors. This helps them to adapt their own behaviors appropriately according to the situation, and consequently, to interact more effectively with people from a culturally different society.

3) *Motivational CQ* provides the important drive for users to persist in intercultural interactions. Users with a high motivational CQ are likely to direct more energy toward learning and understanding cultural differences. They are likely to persist and practice new behaviors even when faced with challenges.

4) *Behavioral CQ* enables users to enact appropriate behaviors. Effective intercultural interactions require users to possess a high behavioral CQ and to enact the desired behaviors. Effective intercultural interactions require competences in both verbal language and nonverbal behaviors such as gestures and displays of emotion. Individuals with a high behavioral CQ are able to adapt to their situation and display the appropriate behaviors.

D. Cultural Intelligence and Business

Business is becoming increasingly globalized, and partnerships are a means to gain a competitive advantage. We believe that cultural differences have a greater impact on cross-cultural business efficiency than previously thought. Cultural backgrounds influence how people think, act and interpret information during business activities. Thus, the potential for success or failure depends on the ability of organizations and leaders to make appropriate decisions within a framework of cultural diversity. Businesses and leaders must understand and become proficient in intercultural communication. In this regard, CQ offers strategies to improve cultural perception and to make it possible to understand the culturally motivated behavior of individuals, companies and organizations. Many articles [24] [25] [26] address the importance of CQ and culture in the context of international business [27] [28] [29]. Huber [30] indicates that the performance of an international business, in terms of efficiency and effectiveness, is determined by the quality of its organizational intelligence. Ang and Andrew [31] specify that organizational intelligence is the CQ of businesses. CQ in business is based on the research on psychology concerning the CQ of individuals, as well as on the views of the organizations. CQ permits businesses to collect a set of resources and to develop their capabilities. Ang and Andrew suggest that, when organizations venture into foreign territories, CQ is a necessary predictor of organizational performance. The involvement in international trade offers significant advantages and challenges to the business development of a company. A business may be successful at home because of its cultural sensitivity. However, this does not guarantee that it will be able to attract international suppliers, partners and customers. If the business does not learn to adapt to cultural differences, it risks losing and missing business opportunities. A business approach that is culturally inappropriate may be detrimental when doing business abroad. Knowledge and sensitivity toward other cultures result in increased business success. Consequently, CQ is of the utmost importance when engaging in international business practices.

In sum, research on CQ has provided a new perspective and presented a new way to alleviate cross-cultural businesses challenges. This research aims to invent a CQ computational model in order to process cultural knowledge and to support international business decision-making processes.

E. Development of our Conceptual Model

Making a good cross-cultural business decision depends on many factors. In the past, cultural scholars used CQ only to evaluate an individual's ability to adapt to cultural diversity. In this study, we consider the cultural factor, which is the effect of CQ on business decision-making processes. Thus, the concept of CQ is for the first time extended in order to assess cross-cultural business decision making. Business decisions with a high CQ are expected to have a more effective performance in and adjustment to multicultural situations.

Sternberg et al. [11] state that general intelligence has four dimensions, i.e., Metacognition, Cognition, Motivation and Behavior. They consider the correlation between the four dimensions as an entity and take full account of their integrity because of their interdependence. Therefore, we assume CQ should also include and consider its four dimensions and their correlation. We agree that the four dimensions of CQ are critical factors that can help individuals, companies and organizations to overcome cross-cultural challenges. Thus, the result of the main theories we developed from this study is that the diverse structures of CQ should be considered collectively in order to integrate the elements required to respond to the cultural knowledge acquired and to respect the decision-making process in cross-cultural business activities. Therefore, we created a CQ conceptual model in order to complete the theories of CQ and the decision-making process required.

We present our model as a whole aggregate multidimensional construct by considering the following conditions: (1) the entire construct considers that the four CQ dimensions occupy the same important level in conceptualization; and (2) the four CQ dimensions form the construct. In sum, in our research we put forward the cognitive theory that the metacognitive CQ, cognitive CQ, motivational CQ and behavioral CQ are four interrelated components built into the CQ, and we integrate our theory into the model (see Fig. 2).

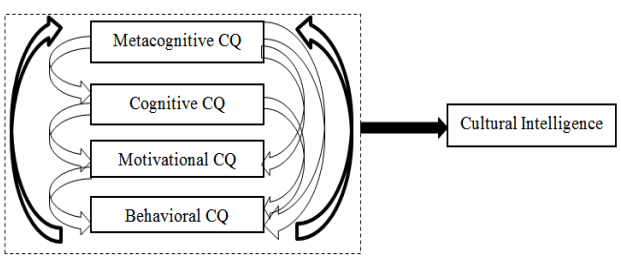


Figure 2. Cultural intelligence conceptual model

This conceptual model proposes a cyclical process of CQ decision making in four stages, while respecting the correlation and interdependence between the four dimensions: (1) It observes the behaviors, promotes active thinking and drives individuals to adapt and revise their strategies in different cultural settings; (2) It acquires and understands the knowledge that can influence individuals' thoughts and behaviors; (3) It considers the implications and emotions associated with cultural settings, and it drives efforts and energy toward effective functioning in a new culture; and (4) It transfers knowledge through verbal and nonverbal behaviors to the culturally diverse situations. This process enables us to identify the elements of the global CQ so we may apply it as a whole, regardless of whether these dimensions are decision variables or other measurable parameters. In this process, we adopt a holistic approach that does not aim to reduce the model to its individual components.

III. CHOICES OF AI TECHNOLOGIES

Individuals, companies and organizations need research combining CQ and AI to support them in decision making in international business. We have not yet found any research that attempts to combine AI and CQ in the context of using CQ knowledge to develop a business intelligent system. This is a gap in the present research. Below, we present how our work meets the challenge of filling the gap between AI and CQ studies for business decision-making support.

A. AI Technologies

We make use of technology solutions to invent a computational model based on our conceptual CQ model with many complex behaviors without degrading the conceptual model's overall quality of human-like thinking in business activities. Business intelligence generally involves two types of data: the first type consists of traditional crisp values, or numbers; the second type is uncertain, incomplete and imprecise. This information is presented in a manner that reflects human thinking and is called "soft data." When we introduce the cultural concept to cross-cultural business activities, we usually use soft information represented by words rather than traditional crisp numbers. The traditional computational technique, known as "hard" computing, is based on Boolean logic and cannot treat cross-cultural business soft data. In order to enable computers to emulate a way of thinking that resembles that of humans, and in order to improve CQ soft data interpretation, we first used fuzzy logic to design the computational model. This technology is capable of operating with uncertain, imprecise and incomplete information. It attempts to model a human-like understanding of words in decision-making processes. Fuzzy logic technology is used for three reasons: (1) 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*." (2) 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 [32]. (3) Fuzzy logic provides a wide range of business cultural expressions that can be understood by computers.

Although fuzzy logic technology has the ability and means to understand natural language, it offers no mechanism for automatic rule acquisition and adjustment. To remedy this defect, the second technology that we

choose is the Artificial Neural Network (ANN). ANN presents a viable solution for processing incomplete and imprecise business cultural information. ANN can learn from historical business cultural cases and manage new data input and CQ generalization rules of acquired knowledge automatically. ANN technology is used for two reasons: first of all, it can be used to extract hidden CQ knowledge in large quantities of cultural data; second, ANN can also be used to correct CQ fuzzy rules. In other words, where acquired CQ knowledge is incomplete, ANN can refine the knowledge, and where CQ knowledge is inconsistent with some given cultural data, neural networks can revise the CQ rules. In our computational model, ANN technology avoids the tedious and expensive processes of CQ knowledge acquisition, validation, and revision.

Fuzzy logic and ANN are complementary paradigms in our computational model. This hybrid neuro-fuzzy technology makes use of the advantages and power of fuzzy logic and of ANN. The soft-computing technology infers the characteristics of the CQ in an environment of cultural diversity and invents an updated computational model taking into account the CQ knowledge. This soft-computing technology is able to reason and learn in an uncertain and imprecise cultural environment. Soft-computing technology represents the essence of our computational model.

Furthermore, because this hybrid technology is applied to our computational model, the model represents both a symbolic approach and a connectionist approach. CQ symbol representations are the product of human cultural work, which means that there is direct access to semantic CQ knowledge. CQ knowledge about the external cultural world is abstracted via perception and represented using a symbolic framework. We use CQ symbol manipulation processes to equip the model and logical rule-based approaches to apply to the model. The CQ symbols are interpreted and reasoned about by using fuzzy logic technology. This technology for CQ symbolic representation mechanisms allows the model to reason about the external cultural world. This method easily and efficiently adapts and interacts with the external world, predicts the future and uses reasoning capabilities.

The connectionist approach that we use in the model is ANN; it is the construction of skills through a self-organizational (behavioral) process in which the model interacts in real time with its environment. In the connectionist approach, the model depends on the parallel processing of non-symbolic distributed activation patterns. Contrary to the rule-based fuzzy logic that we used in the symbolic approach, statistical methods are applied in order to process information in this part.

B. Linguistic Variables and Fuzzy Rules

The concept of fuzzy logic is not only a technology but also a new philosophical concept in the cultural domain. At the heart of fuzzy logic lies the concept of a linguistic variable. The idea of linguistic variables is one basis of the fuzzy set theory. A linguistic variable is a fuzzy variable. The cultural values of linguistic variables are words rather than numbers. For example, when we say "*Cultural Intelligence is high*," it means that the linguistic variable of CQ takes the linguistic value *high*. We use IF-THEN fuzzy rules to incorporate the knowledge of human cultural experts. Thus, our linguistic variables are used in fuzzy rules. 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 fuzzy set operations used in our system are *Intersection* and *Union*. For example, the fuzzy operation used to create the *Intersection* of two fuzzy sets A and B is as follows:

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

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

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

The fuzzy sets are shown in Fig. 3. Each universe of discourse consists of three fuzzy sets: *Low*, *Medium* and *High*. As we can see in Fig. 3, a person who has a score of 6.8 in fuzzy logic has a membership in the '*High*' set with a degree of 0.2. At the same time, he/she has also a membership in the '*Medium*' set with a degree of 0.15 This means that a person with a score of 6.8 adheres partially to several sets.

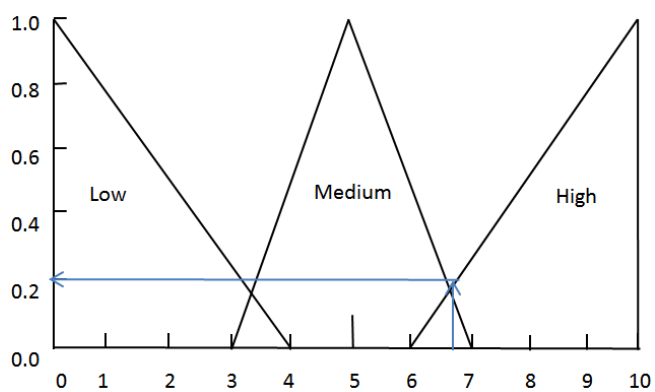


Figure 3. Three fuzzy sets: Low, Medium, and High fuzzy sets

As we explained above, our hybrid neuro-fuzzy computational model uses AI technologies and combines the advantages of fuzzy logic and ANN. It can be trained to develop IF-THEN fuzzy rules. CQ expert knowledge is easily incorporated into the structure of the neuro-fuzzy model. At the same time, the connectionist structure prevents fuzzy inference, which would entail a substantial computational burden.

CQ decision making is often based on the intuition, common sense and experience of experts. A large number of

fuzzy rules provide us with a means of modeling how experts make decisions in cross-cultural activities. Based on these rules, users' decisions can be evaluated and appropriate suggestions can be offered by the system.

IV. DESIGNING THE CULTURAL INTELLIGENCE COMPUTATIONAL MODEL

In this section, we explain how to extract cultural information from a business decision-making process and how to assess decisions through our CQ computational model. The purpose of creating our computational model is to help users make decisions in cross-cultural activities.

A. Computational Model

On the basis of our whole aggregate multidimensional CQ conceptual model (see Fig. 2), we computerize this CQ conceptual model into a CQ computational model.

The model is a multilayer neural network that is functionally equivalent to a fuzzy inference model. It uses a technique called the fuzzy inference method by Mamdani [33]. Fig. 4 illustrates an example of the application of this technique in the model through the use of triangular sets.

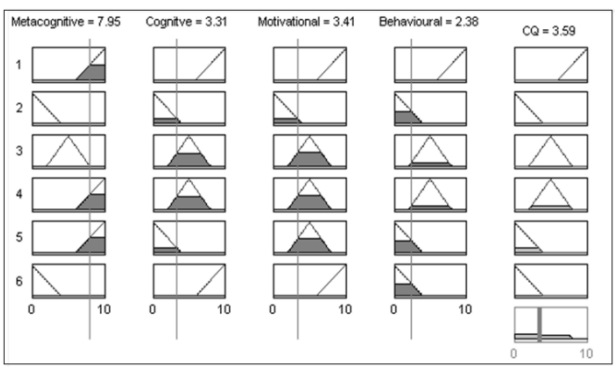


Figure 4. Example of Mamdani-Style fuzzy inference using triangular sets

We define the fuzzy inference model as having four crisp inputs: *Metacognitive CQ*, *Cognitive CQ*, *Motivational CQ* and *Behavioral CQ*, and as having one output: CQ. For example, input metacognition is represented by metacognitive fuzzy sets 1, 2, 3, 4, 5, and 6; output CQ is represented by fuzzy sets CQ 1, 2, 3, 4, 5, and 6. Each row represents a rule; each column represents a crisp input which determines the degree to which these inputs belong to each of the appropriate fuzzy sets.

Fig. 5 shows the neuro-fuzzy model that corresponds to this fuzzy inference model. It is represented with a neural network composed of five layers in the model. Each layer of the network is associated with a particular step in the fuzzy inference process by Mamdani [33]. We also have four inputs in our computational model: Metacognitive CQ, Cognitive CQ, Motivational CQ and Behavioral CQ, and one output: CQ.

We explain the network inference process of the computational model as follows:

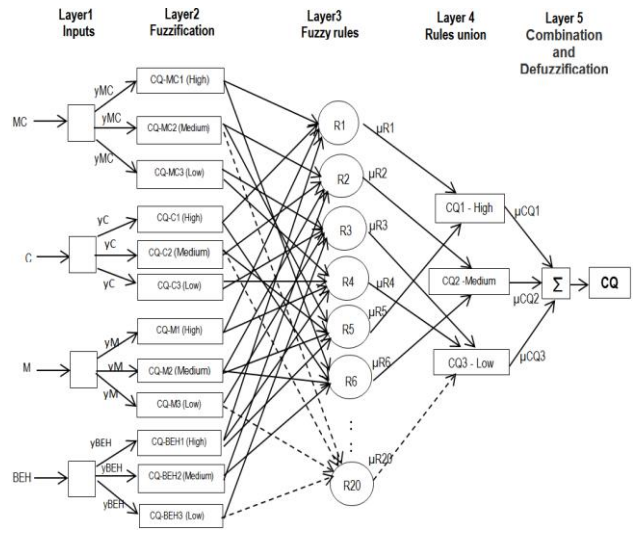


Figure 5. Computational model of cultural intelligence for decision making

Layer 1 - Inputs: 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.

Layer 2 - Fuzzification: Each neuron corresponds to a business CQ linguistic label (e.g., *High*, *Medium* and *Low*) associated with one of the input CQ variables in Layer 1. In other words, the connection of the output, which represents the membership value, specifies the degree to which the input CQ values belong to the neuron's fuzzy set. The connection is computed at this layer.

Layer 3 - Fuzzy Rules: The output of a neuron at this layer is the cultural fuzzy rules. Each neuron corresponds to one CQ fuzzy rule. The CQ fuzzy rule neurons receive inputs from Layer 2, which represent CQ fuzzy sets. For example, neuron R1 represents CQ rule 1 (Rule 1: *IF metacognition is high AND cognition is high AND motivation is high AND behavior is high THEN CQ is high).* Neuron R1 receives input from the neurons *CQ-MC1 High*, *CQ-C1 High*, *CQ-M1 High and CQ-BEH1 High*.

Layer 4 - Rules Union (or consequence): At this layer, neurons have two main tasks: (1) to combine the precedent of CQ rules; and (2) to determine the output level (*CQ1-High*, *CQ2-Medium* and *CQ3-Low*).

Layer 5 - Combination and Defuzzification: This layer combines all the consequential rules and computes the crisp output after defuzzification. The composition method "sum-product" [34] 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 computational model, which is the simplest calculation of the fuzzy set as shown in Fig. 6.

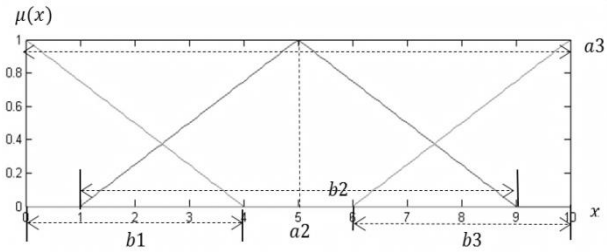


Figure 6. Calculation of cultural intelligence fuzzy sets

The calculation formula (see Equation (3)) of the weighted average of the centroids of the clipped fuzzy sets *CQ3 (Low)*, *CQ2 (Medium)* and *CQ1 (High)* is calculated.

$$y\ (Cultural\ Intelligence) = \frac{\frac{1}{3}b_1^2\mu 1 + a_2 b_2 \mu 2 + \left(a_3 - \frac{1}{3}b_3\right) b_3 \mu 3}{b_1\mu 1 + b_2\mu 2 + b_3\mu 3} \quad (3)$$

where a_2 and a_3 are the respectively center of the medium and high triangles; b_1, b_2 and b_3 are the widths of fuzzy sets, which correspond to *CQ 3*, *2* and *1*.

In Fig. 7, we present the first input (MC) of Fig. 5 in order to explain the process of obtaining the value of the Metacognitive CQ dimension. The other three dimensions, i.e., Cognitive CQ, Motivational CQ, and Behavior CQ, follow the same process.

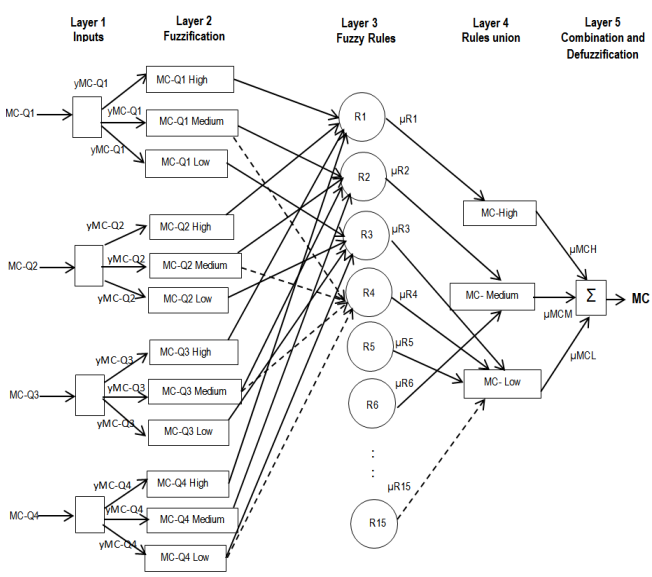


Figure 7. Example of inference to obtain the Metacognition value in the computational model

Fig. 7 shows the neuro-fuzzy model that also respects the fuzzy inference model, which has four inputs *MC-Q1*, *MC-Q2*, *MC-Q3* and *MC-Q4*. The model is composed of five layers. Each layer of the neural network is associated with the same steps in the fuzzy inference process by Mamdani [33].

In detail, a business decision in the metacognitive dimension can be devised using four aspects. The four aspects are expressed in natural language as follows: 1) This decision is conscious of the cultural adaptation it uses when interacting with people with different cultural backgrounds; 2) This decision adjusts its cultural adaptation as it interacts with people from a culture that is unfamiliar to it; 3) This decision is conscious of the cultural adaptation it applies to cross-cultural interactions; 4) This decision checks the accuracy of its cultural adaptation as it interacts with people from different cultures. Thus, we have four inputs to the model, which represent these four aspects in the metacognitive dimension, and one output: Metacognition (MC).

Layer 1 - Input: Four inputs represent the answers of four aspects of users in metacognitive dimension. For example, MC-Q1 is the aspect 1 of Metacognitive CQ**.** These four input variables correspond to four neurons (*MC-Q1*, *MC-Q2*, *MC-Q3* and *MC-Q4*), and are transmitted directly to the next layer, which is expressed as:

$$yi^{(1)} = xi^{(1)},\ i = MC-Q1; MC-Q2; MC-Q3; MC-Q4 \quad (4)$$

where, $xi^{(1)}$ are the four inputs; $yi^{(1)}$ is the output of the four input neurons.

Layer 2 - Fuzzification: For simplicity, each user answer is divided into three fuzzy sets. For example, for aspect 1, the input *MC-Q1* is represented by three fuzzy sets *MC-Q1 High*, *Medium* and *Low*. Three other inputs also respect this principle, which is represented by the same three fuzzy sets *High*, *Medium* and *Low*. We have 12 neurons in this layer. Each neuron receives a crisp input and determines the membership degree to which this input belongs to the neuron's triangular fuzzy set. A triangular membership function by two parameters {a, b} is specified as follows:

$$y_i^{(2)} = \begin{cases} 0 & if\ x_i^{(2)} \le a - \frac{b}{2} \\ 1 - \frac{2|x_i - a|}{b}, & if\ a - \frac{b}{2} < x_i^{(2)} < a + \frac{b}{2} \\ 0 & if\ x_i^{(2)} \le a + \frac{b}{2} \end{cases} \quad (5)$$

$$i = MC-Q1; MC-Q2; MC-Q3; MC-Q4$$

where *a* and *b* are parameters that control the center and the width of the triangle, $xi^{(2)}$ is the input, and $yi^{(2)}$ is the output.

Layer 3 - Fuzzy Rule: Every single neuron in this layer represents a metacognitive fuzzy rule. For example, *R1* corresponds to Rule 1. The value of *yR1* is the output of fuzzy rule 1; it also represents the strength of *R1*. The rule is calculated by the fuzzy operation *Intersection*; therefore, the output of neuron *yR1* is obtained as:

$$yR1^{(3)} = \mu MC\_Q1H \times \mu MC\_Q2H \times \mu MC\_Q3H \times \mu MC\_Q4H = \mu R1 \quad (6)$$

where $\mu MC\_Q1H, \mu MC\_Q2H, \mu MC\_Q3H, \mu MC\_Q4H$ are the inputs and $yR1^{(3)}$ is the output of metacognitive fuzzy rule neuron *R1*.

Layer 4 - Rules Union: The neurons in this layer receive inputs from the corresponding metacognitive fuzzy rule neurons from Layer 3 and combine them. The output of the *MC* is also expressed by fuzzy sets *MC High*, *Medium* and *Low*. The fuzzy operation we use is *Union*. For example, the *Medium* of *Metacognition (MCM)* is expressed as:

$$yMCM^{(4)} = MAX(\mu R2, \mu R6) = \mu MCM \qquad (7)$$

where $\mu R2, \mu R6$ are the inputs and $yMCM^{(4)}$ is the output in Layer 4.

Layer 5 - Combination and Defuzzification: Each neuron represents a single output of the network. We need to combine them into a single fuzzy set. The combined output fuzzy set must be defuzzified. Here, we use the same calculation and principle as for the CQ to calculate Metacognition; the formula is given as follows:

$$y\ MC = \frac{\frac{1}{3}b_1^2\mu MCH + a_2 b_2 \mu MCM + \left(a_3 - \frac{2}{3}b_3\right) b_3 \mu MCL}{b_1\mu MCH + b_2\mu MCM + b_3\mu MCL} \qquad (8)$$

where *MCH* represents the metacognitive *High*, *MCM* represents the metacognitive *Medium*, and *MCL* represents the metacognitive *Low*.

The section above describes our basic concept computational model. Applying fuzzy set theory, many similar fuzzy inference styles have been built, such as Mamdani-style and Sugeno-style. However, in this real practical research, many computational bottlenecks are needed to break through when implementing fuzzy inference process in a neural network.

B. Supervised Learning

One of the main properties of the model is supervised learning, which has the ability to learn from CQ expert experiences and to improve performance by modifying the CQ rules through learning. Supervised learning involves cultural inputs and cultural outputs that are available to our multilayer neuro-fuzzy network. The task of the network is to predict or adjust inputs to the desired outputs.

This multilayer neuro-fuzzy network can apply standard learning algorithms, such as back-propagation, to train it. The network offers a mechanism for automatic IF-THEN rule acquisition and adjustment. This mechanism is very useful, especially in situations where cultural experts are unable to verbalize the knowledge or problem-solving strategy they use.

The principle of the back-propagation algorithm in supervised learning in our model is that we provide the model with the final external CQ data that supervised learning requires; these data represent the results of a user's decision. Each case contains the original input cultural data and the output data offered by CQ human experts to be produced by the model. The model compares actual output with the CQ experts' data during the training process. If the actual output differs from the data given by experts in the training case, the model weights are modified.

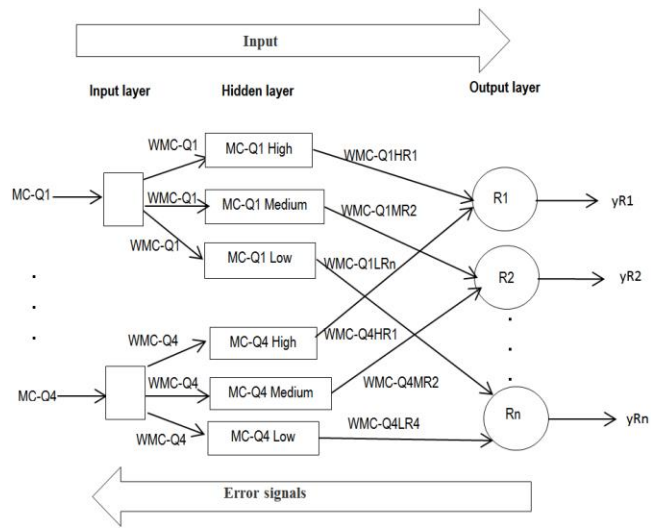


Figure 8. Back-propagation in CQ Neuro-Fuzzy network learning

Figs. 5 and 7 explain neuro-fuzzy inference structure. Fig. 8 shows how to train this neuro-fuzzy network. It is from one part of our Fig. 7 with three layers (Input layer, Hidden layer and Output layer), as an example to illustrate how the neuro-fuzzy network learns by applying the back-propagation algorithm. *MC-Q1* and *MC-Q4* refer to neurons in the input layer; *MC-Q1High*, *MC-Q2 Medium* and *MC-Q1Low* refer to neurons in the hidden layer; and *R1*, *R2* and *Rn* refer to neurons in the output layer. We explain our model's learning process theory in three steps as follows:

Step 1 - Input Signals: We input signals from *MC-Q1* to *MC-Qn* into the model; these signals are propagated through the neuro-fuzzy network from left to right, while the difference signals (or error signals) are propagated from right to left.

Step 2 - Weights Training: To propagate difference signals, we start at the output layer and work backward to the hidden layer. The difference signal at the output of neuron *R1* at sequence *s* is calculated as follows:

$$D_{R1}(s) = y_{e,R1}(s) - y_{R1}\ (s) \qquad (9)$$

where $y_{e,R1}(s)$ is the cultural experts' desired output data of neuron *R1* at iteration *s*. $D_{R1}(s)$ is the difference between the output $y_{R1}\ (s)$ and the experts' desired output data at iteration . For example, we use a forward procedure method to update the CQ rules' weight $W_{MC-Q1HR1}$. Rule *R1* for updating weight at the output layer at iteration *s* is defined as:

$$W_{MC-Q1HR1}(s+1) = W_{MC-Q1HR1}(s) + \Delta W_{MC-Q1HR1}(s) \quad (10)$$

where $\Delta W_{MC-Q1HR1}(s)$ represents the weight correction of the *MC-QHR1* at iteration *s*.

Step 3 – Iteration: We increase iteration *s* by one and repeat the process until the preset difference criterion is satisfied.

Following the above three-step learning procedure, we give a concrete example to show how the model obtains the desired value after learning. Suppose we have collected five people's input data, and get five corresponding CQ results from the output of the model as: y = [5, 6, 7, 3, 2]. On the other hand, the cultural experts give five desired CQ output values as: yd = [7, 7, 6.5, 4.5, 7]. We now use these five pairs of input data and desired values to train the model.

We use this example with two different training algorithms to compare how the computational model learns. This approach facilitates the comparison of the results of two different algorithms that we used in our training process. The first algorithm considers the balance of the five-layer network and the generalization of the model. As shown in Fig. 9, after the training with 10 epochs (an epoch is the presentation of an entire training set to the model during training.) The vertical axis (Training-Blue) represents the difference (or error) between the system outputs and the targets.

```
>> net=mycreat(7);

t =

    7.0000    7.0000    6.5000    4.5000    7.0000

>> net=mytrain2(net,p2,t);

TRAINLM, Epoch 0/100, MSE 41.2922/0, Gradient 7.85865/1e-020
TRAINLM, Epoch 10/100, MSE 0.583818/0, Gradient 2.26785e-016/1e-020
TRAINLM, Maximum MU reached, performance goal was not met.

>> sim(net,p2)

ans =

    7.0620    5.5925    7.4443    4.3537    7.1457

>> t

t =

    7.0000    7.0000    6.5000    4.5000    7.0000

>> t-sim(net,p2)

ans =

   -0.0620    1.4075   -0.9443    0.1463   -0.1457
```

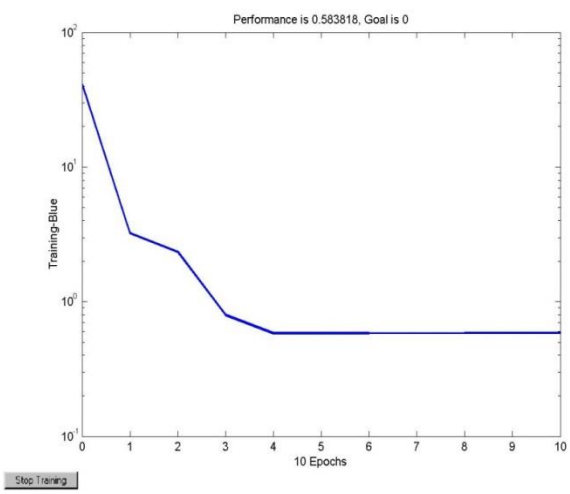


Figure 9. Learning algorithm 1 in computational model

However, the model learns very slowly. The computational model stops learning after 10 epochs, and the model reproduces five final results that still differ from the desired CQ output values. For example, the first desired data requires 7; after training, the model shows the training result 7.062, with a difference of -0.0620. Thus, as the message shows, our performance goal has not quite reached the desired value.

We use the second algorithm to train the model. This training method does not consider the balance of the neuro-fuzzy network and the generalization of the model. After 9 epochs training processes, we get the new output from the model as: y = [7, 7, 6.5, 4.5, 7], shown in Fig. 10.

```
>> net=mycreat(7);

>> net=mytrain3(net,p2,t);

TRAINLM, Epoch 0/9, MSE 45.2964/0, Gradient 13.567/1e-010
TRAINLM, Epoch 9/9, MSE 1.65969e-022/0, Gradient 4.16374e-012/1e-010
TRAINLM, Maximum epoch reached, performance goal was not met.

>> sim(net,p2)

ans =

    7.0000    7.0000    6.5000    4.5000    7.0000

>> t

t =

    7.0000    7.0000    6.5000    4.5000    7.0000
```

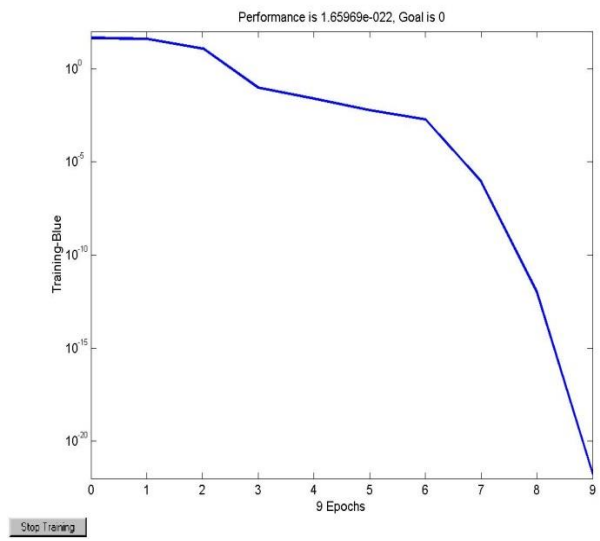
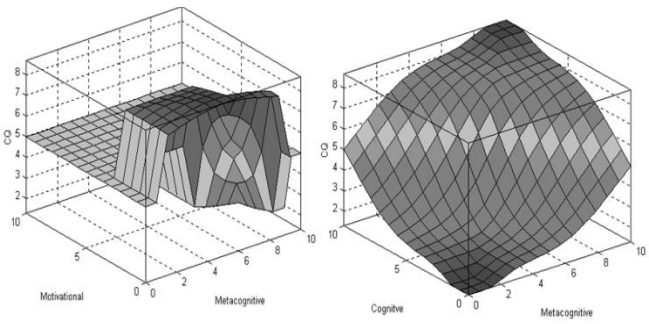


Figure 10. Learning algorithm 2 in computational model

The output of the model quite accurately resembles the desired CQ values yd = [7, 7, 6.5, 4.5, 7] from the cultural experts, and we believe our computational model has reached the training goal, that is to say, the model has the ability to learn new CQ knowledge.

In this model, we only change the weights following the fuzzy rules layer. In order to prevent an overfitting problem, we prefer the algorithm 1. However, a detailed description of learning algorithms is beyond the scope of this paper. The algorithm criterion is that it not only guarantees training speed but also considers balance and generalization in our neuro-fuzzy computation model. Fig. 11 shows another graphic in three dimensions that demonstrates how the neuro-fuzzy network converts bad rules weights into the desired CQ rules weights.



a) Bad rules b) Desired rules

Figure 11. Example of the result after supervised learning

V. IMPLEMENTING THE MODEL IN AN EXPERT SYSTEM

This section presents the general conceptual structure of our system, which includes three parts. First, we explain why we implemented our computational model in an expert system. Second, we describe the structure of the system. Third, we provide details of the CQ domain by collecting and analyzing both data and knowledge thus making key concepts of the system design more explicit.

A. *Why an Expert System*

In the preceding sections, we presented the two basic premises of our computational model through the application of soft computing: (1) to study the thought processes of human cultural experts; (2) to represent these thought processes for computer use; and (3) to be capable of acquiring, extracting and analyzing the new knowledge of cultural experts. In this section, we want the system should be able to express knowledge in a form that is easily understood by users and deal with simple requests in natural language rather than a programming language. Second, the system should act as would an efficient team of cultural experts capable of making decisions and providing explanations in the decision-making process in culturally diverse settings. Hence, we integrated the computational model into an expert system, which is designed to mimic the decision making of human experts [35] [36].

B. *Cultural Intelligence Decision Support System*

The system is called the Cultural Intelligence Decision Support System (CIDSS). The CIDSS represents CQ knowledge through the heuristic manipulation of a CQ database center. The CIDSS has three application domains: *Business Activities*, *Expatriate Assignments* and *Business Project Evaluation*. Fig. 12 illustrates the general structure of the CIDSS. The structure includes four main modules:

1) The CQ Computional Model contains CQ knowledge that is useful for solving business cultural problems. The *Cultural Intelligence Model* in this structure is represented by the trained neural-fuzzy network. This module supports all the cultural decision-making steps in the system. It connects with three different units: *New Data*, *Training Data* and the *Cultural Intelligence Database Center*. *New data* include users' requests for solving a given problem that involves cultural business affairs. *Training Data* are a set of training examples that are used for training the network during the learning phase. *The Cultural Intelligence Database Center* predominantly contributes to the knowledge gathered from the data about different cultural aspects, which have been collected from different countries.

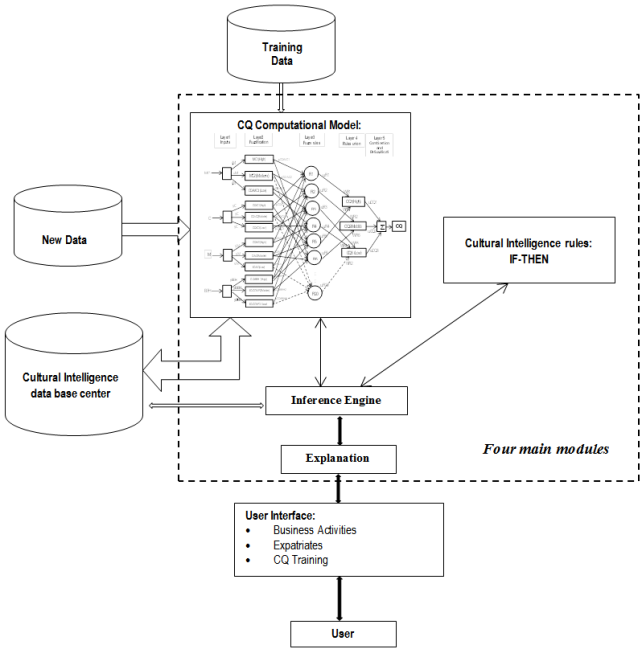


Figure 12. General deployment structure of CIDSS

2) The Cultural Intelligence IF-THEN Rules examine the CQ knowledge base, which is represented by the computational model, and produce rules which are implicitly "buried" in the neuro-fuzzy network.

3) The Inference Engine is the core of the CIDSS. It controls the flow of business cultural information in the system and initiates inference reasoning from the CQ knowledge base. It also concludes when the system has reached a decision.

4) The Explanation clarifies to the user why and how the CIDSS has achieved the specific business cultural decsions. These explanations include analyses, advice, conclusions and other facts required for deep reasoning.

As a hybrid intelligent system, it provides comprehensive and global solutions and forms a system of rules capable of adapting to a multicultural environment. This is the context in which the CIDSS was born. We combined two intelligent technologies: hybrid neural-fuzzy and expert system. The hybrid neural-fuzzy technology ensures that the CIDSS is capable of reasoning and learning in an uncertain and imprecise business cultural environment. The expert system, meanwhile, uses the knowledge of cultural experts and inference procedures in order to solve difficult problems normally requiring human expertise in the

CQ domain. This synergy improves adaptability, fault-tolerance robustness and speed of system.

The CIDSS possesses generic CQ and is not specific to a particular culture, such as that of the United States or China. The system shows big capabilities of cultural adaptation by modeling the human decision-making process in situations characterized by cultural diversity. Furthermore, due to its intricate cultural schemas and analytical abilities, the system can help users identify and understand key issues in cultural judgment and decision making. It also gives them the corresponding explanations. In this research, C/C++ is chosen as the programming language.

C. Data and Knowledge Acquisition

When more CQ knowledge has been collected, the system becomes stronger. CQ Data for the CIDSS are often collected from different sources, there are four different types of data in the CIDSS: (1) incompatible data, which is often the data we want to store in code and numbers in packed decimal format; (2) inconsistent data, which is often the same facts represented differently in CQ databases; (3) missing data, considered as actual cultural data records that often contain blank fields. We usually infer useful information from them and fill in the blank fields with average values; and (4) examples of previous CQ data that we use to train the neuro-fuzzy network. For example, we use a self-assessment questionnaire developed by Ang et al. [4] as the input data to CIDSS. This questionnaire has 20 items that measure CQ and was used to collect data for studies on the test subjects regarding their capacity for cultural adaptation.

In the process of knowledge acquisition in the CQ domain, we collect CQ knowledge by reading books and reviewing documents, manuals, papers, etc. We also collect additional information by interviewing cultural experts. During a number of interviews, cultural experts are asked to identify some typical cases, describe how they solve each case and explain the reasoning behind each solution. However, extracting knowledge from a human expert is a difficult process. Usually, cultural experts are unaware of the knowledge they have and the problem-solving strategy they use and they are often unable to verbalize these. Experts may also provide us with incomplete, inconsistent or irrelevant information. We then analyze the acquired knowledge and repeat the entire process. The example of CQ knowledge acquisition is given in Section III.

VI. CIDSS COGNITIVE ARCHITECTURE

As we mentioned in Section III, the CIDSS uses both the symbolic and the connectionist approaches of AI. The CIDSS respects the cognitive concepts regarding global CQ theories and details how the human mind works in decision-making processes. Noubel [37] considers that a decision-making process follows four major steps and describes how the path from idea to the action is organized in decision making. The sequence is used of the basis of the analysis in our cognitive cycle architecture:

1) *The reflection level:* Intelligence mobilizes and cross-fertilizes available knowledge via a refined synchronous or asynchronous dialogue, either through face-to-face contact or remotely. Dialogues draw on new horizons, allow the anticipation of conflicts, and prepare all decision makers for consensus.

2) *The options formulation level:* This level owes its quality to upstream thinking. This is a sensitive step that requires as much objectivizing of object-links (i.e., projects, threats, needs, etc.) as with elimination processes that require strong knowledge mobilization. It usually leads to a final option.

3) *Selection of the final option:* If steps 1 and 2 are managed with intelligence, then the selection of the final option is much easier. Candidate options are richer, more detailed, more flexible, and ultimately more representative.

4) *The action level:* This level engages new intelligence processes, knowledge interaction and operational coordination between decision makers. The cycle from steps 1 to 4 is permanent and self-inclusive. It functions like an endless spiral.

The CIDSS also relies on engineering concepts in its solutions for the design and implementation of software information. It offers better learning mechanisms, which emulate human intelligence. The CIDSS is a distributed and modular architecture. It relies on the functional "*cultural consciousness*" mechanism for much of its operations. Its modules communicate and offer information to each other.

By using its cognitive cycle, the CIDSS recognizes business-related information in natural language from its complex environment. The CIDSS influences its environment by offering a decision or recommendation to users. Fig. 13 describes the cognitive architecture of CIDSS.

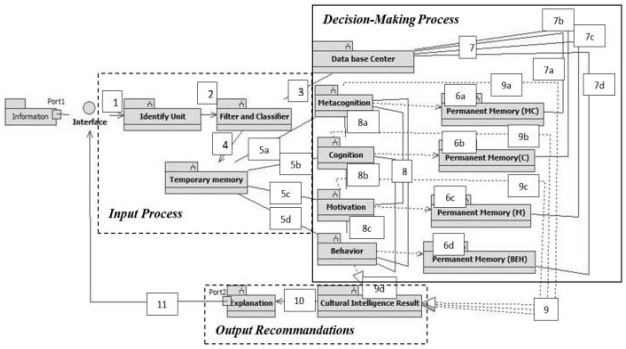


Figure 13. Cognitive architecture of CIDSS

The three main parts of the architecture are: (1) The *Input Process* presents information or a phrase in natural language, which expresses a user's demand via the input of the user interface. Through the *Identify Unit* to distinguish which domain the user wants to consult, the *Filter and Classifier module* takes the inputted information, classifies it, and filters what is not useful for analysis in the next steps; (2) The *Decision Making Process* is a neural network with fuzzy inference model capabilities. The system can be trained to develop IF-THEN CQ fuzzy rules and can

determine membership functions for input and output variables. This module has four sub-modules: *Metacognition (MC)*, *Cognition (C)*, *Motivation (M)* and *Behavior (BEH)*; (3) The *Recommendation* explains the results of decision making to users in natural language and provides suggestions.

The following describes these steps, which correspond to the numbers inside the rectangles in Fig. 13.

Step 1: The business information is in natural language and expresses a problem, a question or a requirement of the user. It is input through the user interface. The information enters the *Identify* module, which identifies the information used to determine what the user requires.

Step 2: The business information goes to the *Filter and Classifier* module. In this module, the information is classified. Useful information is filtered from non-useful information. The useful information is culturally analyzed in the following steps.

Step 3: To perform this classification, the module is associated with the *Cultural Intelligence Database Center*. This center has the necessary data required by the system, such as countries, religions, languages and laws.

Step 4: The classified business 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: Modules 5a-*Metacognitive*, 5b-*Congnitive* 5c-*Motiviational* and 5d-*Behavioral* collect the business 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 behaviour. Each permanent memory represents a complete and specific cultural database that is used by its associated module to analyze the business cultural information stored in the *Temporary Memory*.

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

Step 8: After the analysis has been completed in each module, the four modules interact with each other to adjust their respective cultural decisions. This interaction enables each module to make a complete and effective decision before continuing to the next step.

Step 9: Following the interaction among the modules of the different dimensions of cultural intelligence, 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 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*.

Figs. 14 and 15 present an example of two outputs of the *Expatriate Assignment* application domain that show how the CIDSS can help a user make decisions by taking into consideration his/her inputted request. The CIDSS prototype system follows the decision-making cycle process shown in Fig. 13. The input data are specific business questions in natural language provided by users. The system provides two outputs as answers to the question. Output 1 (Fig. 14) gives a general decision to answer the question put by the user.

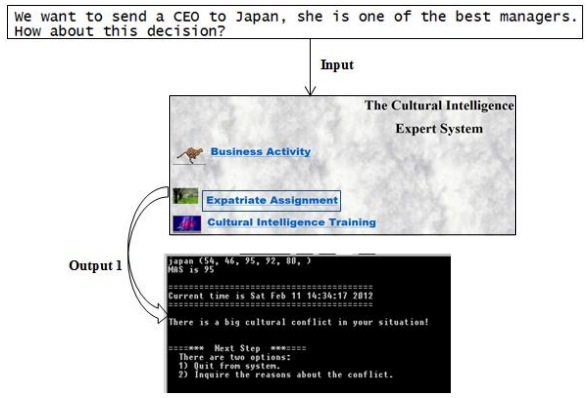


Figure 14. Example of CIDSS prototype system (Output 1)

Output 2 (Fig. 15) provides more detailed explanations, which clarify to the user why the system reached that decision.

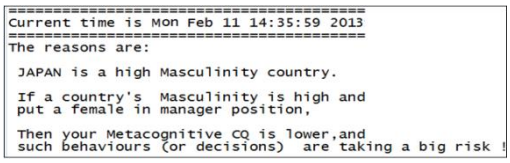


Figure 15. Example of CIDSS prototype system (Output 2)

VII. EVALUATION OF THE MODEL

Three cultural experts have validated our computational CQ model and the CIDSS prototype system. This validation ultimately reflects the consistency between the real world and the artificial CIDSS system. The CIDSS prototype system was also tested with two hundred people by measuring their CQ value. The effectiveness and robustness of the system is evaluated by carrying out a regression analysis on these data. Fig. 16 shows the results of the analysis.

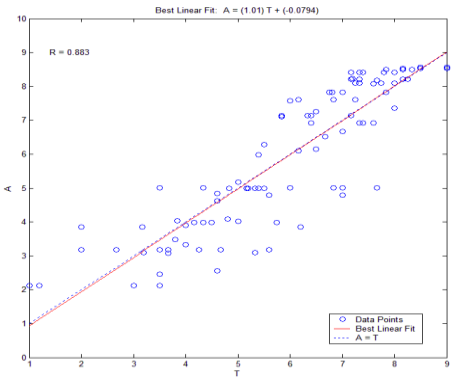


Figure 16. The regression analysis of two hundred people CQ values

The correlation coefficient *R* between the system outputs and the corresponding experts' desired values is calculated, *R*=0.883. After training the system with these data, the final *R* is close to 1. Based on the results of the validation, the cultural experts compared the CIDSS results with their own. These experts concluded that the cross-cultural business decisions recommended by CIDSS are similar to the ones suggested by a human expert.

To date, in the CQ domain, no research on CQ has been empirically computerized. This computational model is first created with soft-computing technology.

We also add CIDSS to self-awareness CQ training programs as an important means of improving the capacity of individuals and organizations to overcome these cross-cultural challenges. It is critical that employees be able to interact effectively with their clients, users, vendors, and other professionals from different cultures in today's global workforce. This new work environment requires employees to acquire new competencies and unique capabilities in order to work effectively beyond traditional cross-cultural training. Within this context, the CIDSS provides important insights about personal capabilities, as well as information on the user's own CQ in culturally diverse situations. Users can get two evaluation (self- and observer evaluations) questionnaires available in the CIDSS in order to compare their results. Figs. 17 and 18 present two parts of a user's results of the self-evaluation questionnaire in the CIDSS. For example, the self-evaluation questionnaire that evaluates the user's CQ is presented in the system as follows:

Result 1: After inputting the answers of the questionnaire to a user's response in the CIDSS, the system provides feedback. If a user's evaluation achieves a high score (e.g., greater than 8), the system displays the following message:

```
=========================================
Current time is Fri Jan 04 18:12:02 2013
=========================================
Your the newest result  is  :
9.5.
Congratulation!! The CQ Evaluation is excellent !!
```

Figure 17. Result 1- High score: Greater than 8

Result 2: When the evaluation results are lower than 6, the system accordingly gives useful suggestions for personal self-development as required. The CIDSS presents recommendations as follows:

```
=========================================
Current time is Fri Jan 04 18:14:44 2013
=========================================
Your the newest results are :
4.9.
****************
   In the future trainning,
  the Systems suggest you that
  you should pay more attenttion to the following aspects
  to improve your CQ ability:

A)In Behavioral
 1) altering your facial expressions when a cross-cultural
interaction requires it.

B)In Motivational
 1) confident socializing with locals in a culture that is
unfamiliar to you.
 2) interacting with people from different cultures.

C)In Metacognitive
 1) the accuracy of cultural knowledge  with people from
different cultures.
```

Figure 18. Result 2- Low score: Lower than 6

This process allows the system first to evaluate the users to identify their problems in the CQ domain. The system then offers several precise recommendations to users based on the results of the evaluation. Moreover, the system uses natural language to give users recommendations in order to provide the users with a stress-free and friendly evaluation environment.

Organizations could also use the CIDSS (both self- and observer evaluations) to train employees for expatriate purposes. At this point, the CIDSS serves as an efficient team of top CQ experts who accompany individuals or organizations that want to have training or insights on how to increase their efficiency in culturally diverse settings.

VIII. CONCLUSION

To keep up with the pace of globalization, international business and traditional BI need to deal with two major issues: how to adapt to cultural diversity and how to deal with "soft data" or natural language in order to make human-like business decisions.

In order to address these issues, this research attempts to build a "culturally aware" system, which helps users make decisions in cross-cultural business activities, and enables users to solve cultural problems that would otherwise have to be solved by cultural experts. Organizations can also use the system to evaluate and train employees by providing them with specific suggestions to improve their weaknesses and develop their cultural skills for expatriate assignments. This latter point is of particular importance in modern learning theories.

The other noteworthy points in this research are the following: (1) this research treats four CQ dimensions as an integrated and interdependent body. As a result, the CQ theories are more complete, more efficient and more precise in their applications. (2) This research fills that gap between CQ and AI. We have made a contribution in the application of AI by computerizing CQ. Consequently, this inventive research provides the opportunity for delving into new research areas and expands the range of intelligence in the field of AI. (3) Furthermore, this research simplifies the work of researchers by freeing them from heavy, complex, repetitive tasks normally carried out manually in the process of CQ studies.

There are some limitations in this research; one of them is that it is confined to CQ domain. In the future, there are still many aspects to improve such as developing a more user friendly interfaces in the commercial version of CIDSS, collecting more multicultural data, integrating CIDSS with other existing systems. Although the limitations, adapting to cultural diversity is a big challenge for the international business and traditional BI where this research has attempted to give an effective answer.

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