INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
ISSN 1841-9836, e-ISSN 1841-9844, 14(6), 653-669, December 2019.

Modeling of Characteristics on Artificial Intelligence IQ Test: a Fuzzy Cognitive Map-Based Dynamic Scenario Analysis

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Abstract: This research article uses a Fuzzy Cognitive Map (FCM) approach to improve an earlier proposed IQ test characteristics of Artificial Intelligence (AI) systems. The defuzzification process makes use of fuzzy logic and the triangular membership function along with linguistic term analyses. Each edge of the proposed FCM is assigned to a positive or negative influence type associated with a quantitative weight. All the weights are based on the defuzzified value in the defuzzification results. This research also leverages a dynamic scenario analysis to investigate the interrelationships between driver concepts and other concepts. Worst and best-case scenarios have been conducted on the correlation among concepts. We also use an inference simulation to examine the concepts importance order and the FCM convergence status. The analysis results not only examine the FCM complexity, but also draws insightful conclusions.
Keywords: fuzzy cognitive Map (FCM), inference simulation, artificial intelligent system, dynamic scenario analysis, IQ Test, linguistic analysis.

1 Introduction

In the academic field, artificial intelligence (AI) is a popular topic. And, many scholar papers and projects focused on this topic [7,33,36]. Also, in industry field, AI-based products are trying to make our lives more convenient and efficient [7]. However, there is a warm debate about whether the emerging AI systems have the potential of helping or doing something devastating to human. To evaluate the smartness of AI systems, Liu et al. paper presents a method to measure the AI system through an IQ test [23]. Based on its measurement framework, a list of 100 AI-based search engines received an IQ score. For example, based on the IQ test result, Google search engine got the highest IQ score of 47.28 [23]. Which means Google's IQ score is almost the same as a six-year-old child's IQ score. These IQ results illustrate that AI-based system still has a long way to go to replace human, at least in industry world.

For the purpose of successfully conducting the IQ test for all the top 100 search engines, such as Google, Bing, Baidu, etc. In 2015, Liu et al. [23] proposed a measurement framework. This framework includes a test bank, which has hundreds of questions. Like a human IQ test, each search engine need to answer several questions that are selected from the developed test bank by random. For each question, they will receive a score between 0 and 100. This framework divides all the questions into four main indicator groups and further into 15 characteristics. Also, a few adult volunteers had the IQ test for the purpose of standardizing the IQ score, and mapping with the human being's IQ score.

Table 1 lists all the 15 IQ characteristics along with their corresponding weights for testing AI systems. After gathering expert opinions (Delphi method), all the 15 weights are calculated and presented in the Table 1.

- C1m (m=1,2...m) = ability to acquire knowledge.
- C2n (n=1,2...n) = ability to master knowledge.
- C3p (p=1,2...p) = ability to innovate knowledge.
- C4q (q=1,2...q) = ability of knowledge feedback.

Table 1: 15 IQ Characteristics for AI system and their corresponding Delphi weights

C1m	**C2n**	**C3p**	**C4q**
C11: Ability to identify word (3%)	C21: Ability to master general knowledge (6%)	C31: Ability to innovate by association (12%)	C41: Word feedback ability (3%)
C12: Ability to identify sound (3%)	C22: Ability to master translation (3%)	C32: Ability to innovate by creation (12%)	C42: Sound feedback ability (3%)
C13: Ability to identify image (4%)	C23: Ability to master calculation (6%)	C33: Ability to innovate by speculation (12%)	C43: Image feedback ability (4%)
	C24: Ability to master arrangement(5%)	C34: Ability to innovate by selection (12%)	
		C35: Ability to innovate by discover laws (12%)	

The proposed IQ test question bank is arranged according to all the 15 IQ characteristics (concepts). To illustrate, an example of testing question: "Please translate 'Technology's impact' into Spanish" should belong to characteristic C22 (Ability to master translation).

The results of Delphi weights are very subjective. Because they are coming from expert's own judgment, which means the results may be biased. Take advantage of linguistic terms from literature sources can be treated as a better method because all the literature publication sources are considered as an objective approach. One of the article's goals is to assign new weights though the fuzzy logic method (an objective approach). Based on the new weights, the interrelations among characteristics also should be investigated. There are some significant relationships among some characteristics. For example, "C21: Ability to master general knowledge" literally has a positive impact on "C24: Ability to master arrangement".

The main method of this research article is a fuzzy logic mathematics method, more specifically, called "fuzzy cognitive mapping" or "fuzzy cognitive map" (FCM). The core idea behind fuzzy logic is that it aims to model the more imprecise reasoning used by humans when they make rational decisions, especially in an uncertain and imprecise environment [14, 37]. By providing a mathematical means of representing vagueness, fuzzy logic models, or sets, are able to recognize, represent, manipulate interdependence between characteristics (concepts).

2 Research method

2.1 Methodology

Fuzzy Cognitive Mapping (FCM) is the most important method of this research article. For the purpose of constructing FCM, the number of edges should be clarified. Theoretically, all the combination of two concepts should have an edge (relationship). However, the literature resources only support the meaningful edges, for example, the edge between one IQ characteristic and the AI system, or the edges of the interrelations among the 15 IQ characteristics. According to the literature resources, it is easy to assign the influence type (negative, positive, or null) of the edge.

Keyword extraction plays a significant role in the relationship between concepts capturing. For instance, one reference paper said concept C22 heavily impacts concept C31, then, keyword "heavily impacts" will be extracted here. Each keyword will be assigned with one of the linguistic terms ("VERY LOW", "LOW", "MEDIUM", "HIGH", and "VERY HIGH"). At least three linguistic terms will be assigned to each edge.

The linguistic terms are fuzzy set problems. The membership function plays a significant role in quantifying the membership grade of the element in X to the fuzzy set [45].

$$\mu_A : X \to [0, 1]$$

Where X represents the universe of discourse while the fuzzy set is A, and μ_A is the membership function [8].

A triangular function will be used in the FCM constructing process. Where a is the lower limit, b is the upper limit, and m is a value between a and b. Figure 1 illustrates the membership function as a graph.

$$\mu_A = \begin{cases} 0, & x \le a \\ \frac{x-a}{m-a}, & a < x \le m \\ \frac{b-x}{b-m}, & m < x \le b \\ 0, & x > b \end{cases}$$

2.2 Linguistic term analyses

The literature resources, support the linguistic term assigning as references. Table 2 summarizes all the possible relationships between each IQ characteristic and the AI system, and the interrelationship among the 15 IQ characteristics. In particular, Barwise's paper mentioned IQ characteristics' ability to identify word is a "most common view" of AI system [24]. Then, the keyword "most common view" will be extracted here, while a linguistic term "HIGH" will be assigned to this edge. Table 2 gives an outline of the linguistic terms, influence type, keywords, and their corresponding reference papers.

In Table 2, "C" represents the "AI system IQ".

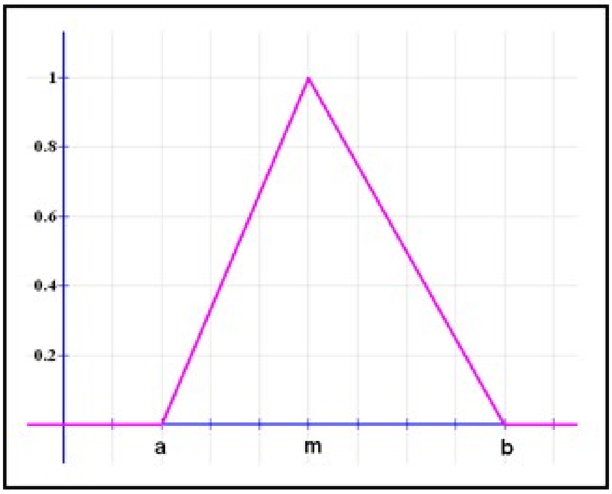

Figure 1: Membership function graph [19]

Table 2: Linguistic terms and their associated references

EDGE OF FCM	KEYWORD	LINGUISTIC TERM	REFERENCE
C11-C	an aspect of	LOW	Lynn et al (2001) [24]
	an aspect of	LOW	Lynn et al (2001) [24]
	an aspect of	LOW	Lynn et al (2001) [24]
C12-C	a key strategic	HIGH	Francisco (2015) [24]
	core capabilities	HIGH	Bernard (2018) [24]
	obvious	LOW	Adam (2016) [24]
C13-C	core capabilities	HIGH	Bernard (2018) [24]
	enable	MEDIUM	Flatworld (2017) [24]
C21-C	important component	HIGH	Bates et al (2003) [24]
	correlated	MEDIUM	Chamorro-Premuzic et al (2006) [24]
	partly represented	LOW	Cattell (1987) [24]
	related to	MEDIUM	Ackerman (2001) [24]
C22-C	no significant correlation	VERY LOW	Moghimi et al (2013) [24]
	week relationship	LOW	Nasimi (2009) [24]
	no interrelationship	VERY LOW	Shangarffam (2009) [24]
C23-C	intersection	LOW	Greenberg (2000) [24]
	accelerate	MEDIUM	Greenberg (2000) [24]
	interleave	MEDIUM	Greenberg (2000) [24]
C24-C	a significant	MEDIUM	Wechsler, D. (1949) [24]
	common view	MEDIUM	APA (1995) [24]
C31-C	interpreted to	MEDIUM	Singh-Manoux et al (2005) [24]
	display	MEDIUM	Schutte et al (2011) [24]
	measures of	HIGH	Ferguson et al (2010) [24]
C32-C	demonstrates	HIGH	Kim et al (2010) [24]
	must entail	VERY HIGH	Gardner et al (1996) [24]
	referred to	HIGH	Sternberg (1985) [24]
C33-C	been central to	VERY HIGH	James (1950) [24]

	fundamental to	VERY HIGH	Leighton et al (2004) [24]
	can be important	HIGH	Bruner (1957) [24]
C34-C	directly	MEDIUM	Sternberg (1981) [24]
	commonly used	MEDIUM	Mayer et al (2007) [24]
	connects to	MEDIUM	Brackett et al (2006) [24]
C35-C	related to	MEDIUM	Teuber et al (1956) [24]
	may affect	LOW	Carroll (1993) [24]
C41-C	are as likely to	LOW	Argyris (1991) [24]
	important element	MEDIUM	Abisamra (2000) [24]
	a key for	HIGH	Jorfi et al (2014) [24]
C42-C	linked to	LOW	Luwel (2013) [24]
	taken into consideration	MEDIUM	FernĂĄndez-MartĂnez (2012) [24]
	is important to	HIGH	Bohland (2010) [24]
C43-C	dominated by	HIGH	Barry (1997) [24]
	driven by	MEDIUM	Messaris (1994) [24]
	result in	HIGH	Roth et al (2005) [24]
C11-C12	statistically significant	MEDIUM	Stanovich et al (1978) [39]
	foundational	VERY HIGH	Stanovich (1991) [40]
	strong connected	VERY HIGH	Nation et al (1998) [30]
C11-C13	improve	MEDIUM	Hull (1994) [17]
	dependent	MEDIUM	Zhu et al (2001) [44]
	benefit	MEDIUM	Wang et al (2001) [43]
C21-C22	important	MEDIUM	Collombat (2006) [9]
	widely identified as	LOW	Collombat (2006) [9]
	never an empty mind of	MEDIUM	Delisle (2003) [13]
C21-C23	result from	HIGH	Baroody (1999) [5]
	partially predicted by	LOW	Cowan (2011) [10]
	as the basis	MEDIUM	Askew (1998) [4]
C21-C24	commonly used	MEDIUM	Rugg et al (1997) [35]
	spontaneously	MEDIUM	Mandler et al (1988) [28]
	related to	MEDIUM	Gopnik et al (1984) [16]
C21-C31	able to	MEDIUM	Feigenson et al (2004) [15]
	a key precursor of	VERY HIGH	De Smedt et al (2009) [11]
	access to	HIGH	De Smedt et al (2011) [12]
C21-C32	according to	MEDIUM	Afuah et al (2003) [1]
	used to	MEDIUM	Afuah et al (2003) [1]
	embodied in	HIGH	Talaya et al (2008) [41]
C21-C33	found to be	HIGH	Scardamalia et al (1992) [38]
	directive effect	MEDIUM	Miyake et al (1979) [29]
	prompted by	HIGH	Bereiter (1989) [6]
C21-C34	facilitate	HIGH	Alexander et al (1995) [3]
	related to	MEDIUM	Qian et al (1995) [34]
	as a basic	MEDIUM	Linnenbrink-Garcia et al (2012) [22]
C21-C35	needed for	MEDIUM	Njoo et al (1993) [31]
	lies in	HIGH	Klahr et al (1988) [18]
	support	HIGH	Van (1988) [42]
C41-C42	statistically significant	MEDIUM	Stanovich (1978) [39]
	foundational	VERY HIGH	Stanovich (1991) [40]

	strong connected	VERY HIGH	Nation et al (1998) [30]
C41-C43	improve	MEDIUM	Hull (1994) [17]
	dependent	MEDIUM	Zhu et al (2001) [44]
	benefit	MEDIUM	Wang et al (2011) [43]
C31-C35	valuable for	MEDIUM	Agrawal et al (1996) [2]
	led to	HIGH	Piatetsky-Shapiro (1996) [32]
	indicate	HIGH	Koperski (1995) [20]
C31-C32	representative	HIGH	Luhn (1958) [25]
	based on	MEDIUM	Luhn (1958) [25]
	significance	MEDIUM	Luhn (1958) [25]

Based on the extracted keyword results, Table 3 is a more advanced tabulation is used to summary keyword information into a table according to their linguistic terms.

Table 3: Categorization of keywords based on linguistic terms

LINGUISTIC TERM	KEYWORD		
VERY LOW	no significant correlation	no interrelationship	
LOW	an aspect of obvious partly represented partially predicted by	week relationship intersection widely identified as	are as likely to linked to may affect
MEDIUM	a field of enable taken into consideration according to needed for connects to directly commonly used directive effect related to as a basic improve	accelerate important never an empty mind of as the basis spontaneously able to used to correlated a significant common view interpreted to	important element display statistically significant dependent benefit valuable for based on significance interleave driven by
HIGH	prompted by most common view facilitate lies in support led to important result in	a key for dominated by result from referred to access to core capabilities embodied in representative	demonstrates can be important a key strategic component measures of indicate found to be
VERY HIGH	must entail been central to	strong connected a key precursor of	foundational

2.3 Defuzzification method

Table 2 and Table 3, present a tabulation of the defined five linguistic terms in the fuzzy set we will use later. The Triangular Membership Function [19] which is shown in Figure 2 means different linguistic terms have different output values.

For the purpose of converting a fuzzified output values into a traditional single crisp value, defuzzification process will be used here [27]. Among the existing defuzzification approaches (COG, COA, BOA, etc.), in this research article, we use the Center of Sums (COS) approach, which is one very useful approach for the defuzzification process [14, 27]. This equation of COS is below:

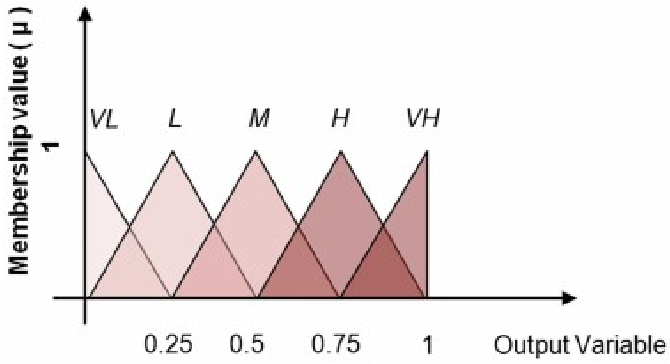

Figure 2: Triangular membership function [19]

$$x^* = \frac{\sum_{i=1}^{N} x_i * \sum_{k=1}^{N} \mu_{A_k}(x_i)}{\sum_{i=1}^{N} \sum_{k=1}^{n} \mu_{A_k}(x_i)}$$

Where n stands for the sum total of fuzzy sets, N is the sum total of fuzzy variables, and, $\mu_{A_k}(x_i)$ is the membership function for the k-th fuzzy set.

3 Data analysis

3.1 Fuzzy cognitive map results

As stated before, each edge, at least three linguistic terms are assigned to, even, for a few edges, four linguistic terms are assigned to.

A standard fuzzy set operation will be used, which is a standard union. Where,

$$\mu_{A \cup B}(u) = max\left\{\mu_A(u), \mu_B(u)\right\}$$

To illustrate, there are the three linguistic terms assigned to the edge of C22-C, they are: "LOW", "VERY LOW", and "VERY LOW".

$A1 = \frac{1}{2} * [(0.25 - 0) + (0 - 0)] * 1 = 0.125$

$A2 = \frac{1}{2} * [(0.5 - 0) + (0.25 - 0.25)] * 1 = 0.25$

$A3 = \frac{1}{2} * [(0.25 - 0) + (0 - 0)] * 1 = 0.125$

The center of area of the fuzzy set C1 is $\bar{x_1} = (0.25 + 0)/2 = 0.125$, similarly, $\bar{x_2} = 0.25$, $\bar{x_3} = 0.125$. Now, the calculated defuzzified value $x^* = \frac{(A_1\bar{x_1} + A_2\bar{x_2} + A_3\bar{x_3})}{A_1 + A_2 + A_3} = 0.1875$.

A final version of the calculated fuzzy cognitive map is presented in Figure. 3. This FCM is drawn with software "Mental Modeler".

The following FCM weights are calculated based on the defuzzified values of the FCM. A summary of the calculation results is presented in Table 4. And, Table 5 provides the corresponding adjacency matrix of the FCM. This matrix can be used to describe the interrelations between the concept.

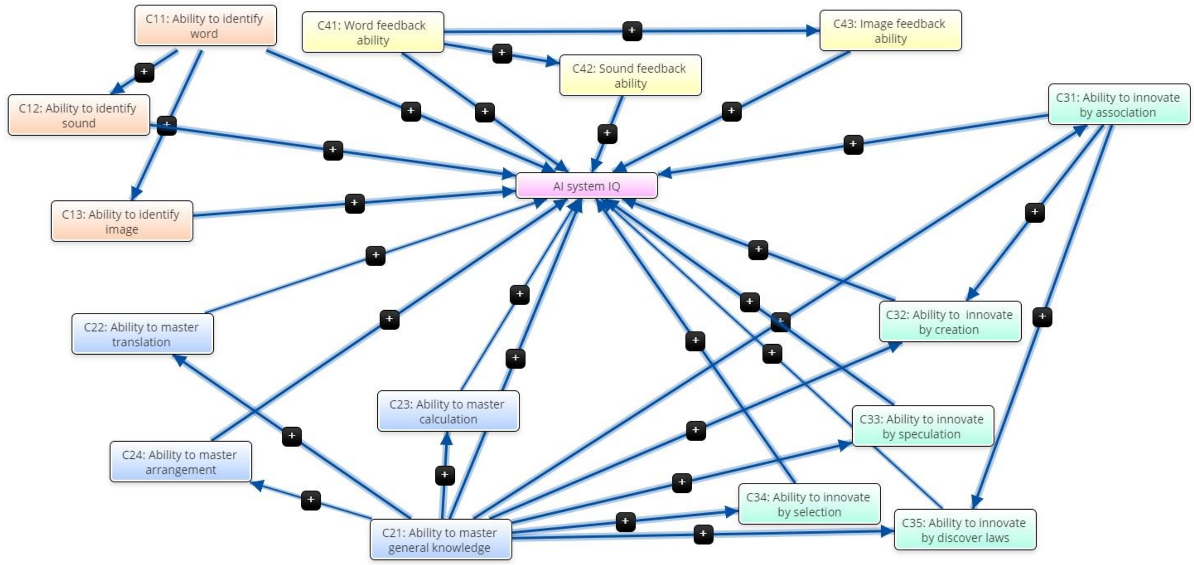

Figure 3: Fuzzy Cognitive Map with positive/negative sign to edges.

Table 4: Edge with its calculated weights

EDGE OF FCM	DEFUZZIFIED VALUE	FCM WEIGHT	DELPHI WEIGHT
C11-C	0.5	6.0373%	3%
C12-C	0.6786	8.1939%	3%
C13-C	0.5833	7.0432%	4%
C21-C	0.5625	6.792%	6%
C22-C	0.1875	2.264%	3%
C23-C	0.45	5.4336%	6%
C24-C	0.5	6.0373%	5%
C31-C	0.6071	7.3305%	12%
C32-C	0.7961	9.6126%	12%
C33-C	0.8125	9.8107%	12%
C34-C	0.5	6.0373%	12%
C35-C	0.4167	5.0315%	12%
C41-C	0.5	6.0373%	3%
C42-C	0.5	6.0373%	3%
C43-C	0.6875	7.3305%	12%
C11-C12	0.6525	N/A	0%
C11-C13	0.5	N/A	0%
C21-C22	0.5625	N/A	0%
C21-C23	0.5	N/A	0%
C21-C24	0.4	N/A	0%
C21-C31	0.7015	N/A	0%
C21-C32	0.6071	N/A	0%
C21-C33	0.6875	N/A	0%
C21-C34	0.6071	N/A	0%
C21-C35	0.6875	N/A	0%

C41-C42	0.6525	N/A	0%
C41-C43	0.5	N/A	0%
C31-C35	0.6875	N/A	0%
C31-C32	0.6071	N/A	0%

Table 5: Adjacency matrix collected from the Fuzzy Cognitive Map

	C11	**C12**	**C13**	**C21**	**C22**	**C23**	**C24**	**C31**	**C32**	**C33**	**C34**	**C35**	**C41**	**C42**	**C43**	**AI system IQ**
C11	0	0.65	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0.5
C11	0	0.65	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0.5
C12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.68
C13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.58
C21	0	0	0	0	0.56	0.5	0.4	0.7	0.61	0.69	0.61	0.69	0	0	0	0.56
C22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.19
C23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.45
C24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5
C31	0	0	0	0	0	0	0	0	0.61	0	0	0.69	0	0	0	0.61
C32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.8
C33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.81
C34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5
C35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.42
C41	0	0	0	0	0	0	0	0	0	0	0	0	0	0.65	0.5	0.5
C42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5
C43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.69
AI system IQ	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

3.2 FCM steady-state analysis

A general descriptive summary about this FCM is shown in Table 6. The connection and component number is not extremely high. All the components can be categorized into the four groups. All the connections are supported by literature references. There are some interdependencies between the components in the same group. Also, there are some interconnections between components of different groups.

Figure. 3, which is the merged FCM, shows the density changed to 0.121 while the average connections per component increased to 1.8125. Hierarchy Index is another complexity measurement of FCM. Hierarchy Index is answerable to all the concepts' out-degree in an FCM of N components [26]. Below is the equation of Hierarchy Index.

$$h = \frac{12}{(N-1)N(N+1)} \sum_{1}^{N} \left[\frac{od(vi) - (\sum od(vi))}{N} \right]^2$$

Where N is the total number of components. And, $od(vi)$ is the row sum of absolute values

Table 6: General FCM statistics

FCM PROPERTIES	**VALUE**
Total components	16
Total connections	29
Density	0.121
Connections per Component	1.8125
No. of driver components	3
No. of receiver components	1
No. of ordinary components	12
Complexity score	0.3333

of a variable in the FCM adjacency matrix.

If h is close to 1, the FCM is supposed to be completely dominant (hierarchical). If h is close to 0, the FCM is supposed to be completely adaptated eco-strategies (democratic) [24]. This FCM's hierarchy index is 0.326, which means, the FCM is much more adaptable to component changes because of its high level of integration and dependence. Also, the in-degree and out-degree of these nodes makes the FCM more democratic, and its system's steady-state more resistant to the alterations of individual components.

The component with the highest centrality was the "AI SYSTEM IQ" with a high score of 8.29. Also, the top three central components directly affecting the "AI SYSTEM IQ" component was the following, in ascending order of their complexity: Ability to innovate by discover laws 1.799, Ability to innovate by association 2.609, and, Ability to master general knowledge 5.319. A higher value means greater importance of an individual concept or several concepts in the overall model.

Table 7: Characteristic, type of concepts, in degree, out degree, centrality and in the FCM

CHARACTERISTIC	**INDEGREE**	**OUTDEGREE**	**CENTRALITY**	**TYPE**
AI system IQ	8.29	0	8.29	receiver
C11	0	1.65	1.65	driver
C12	0.65	0.68	1.33	ordinary
C13	0.5	0.58	1.08	ordinary
C21	0	5.319	5.319	driver
C22	0.56	0.19	0.75	ordinary
C23	0.5	0.45	0.95	ordinary
C24	0.4	0.5	0.9	ordinary
C31	0.7	1.909	2.609	ordinary
C32	1.22	0.8	2.02	ordinary
C33	0.69	0.81	1.5	ordinary
C34	0.61	0.5	1.109	ordinary
C35	1.38	0.42	1.799	ordinary
C41	0	1.65	1.65	driver
C42	0.65	0.5	1.15	ordinary
C43	0.5	0.69	1.19	ordinary

3.3 Dynamic scenario analysis of the AI system IQ

Worst and best-case scenario

The above AI system IQ FCM (Figure 3) shows its complexity. This research also conducted dynamic case scenario analyses along with inference simulation.

To start the analysis, we initially apply the current FCM. Both the worst and best scenario will be examined. After that, some insightful results and conclusions can be made. Based on our knowledge, the worst scenario means all the driver concepts are equal to 0.1. And, the best scenario means all the driver concepts are equal to 1.

From figure 4, we observe that there is approximately 58% increase in the "AI system IQ" in the worst scenario while compared to the initial steady-state scenario as the benchmark. Respectively, the "Ability to innovate by discover laws" has an increase of 13%, the "Ability of innovate by creation" has an increase of 11%. All the other concepts have an increase between 4% and 8%. The results also show that all concepts have a positive causality. Furthermore, all of the slight increases for all the ordinary concepts are related to the small increase of driver concepts.

Alternatively, all the driver concepts can be set as primarily affecting the FCM's ordinary concepts if all the values are set up with 1. From figure 5, we found that the "AI system IQ" in the best scenario while compared to the initial steady-state scenario as the benchmark, has a 100% increase. Similarly, the "Ability of innovate by creation" has an increase of 80%, and the "Ability to innovate by discover laws" has an increase of 75%. All the other concepts have an increase between 38% and 60%. This result also supports the conclusion of positive causality. Based on the results, the "Ability of innovate by creation" and "Ability to innovate by discover laws" has the most significant relevance impact.

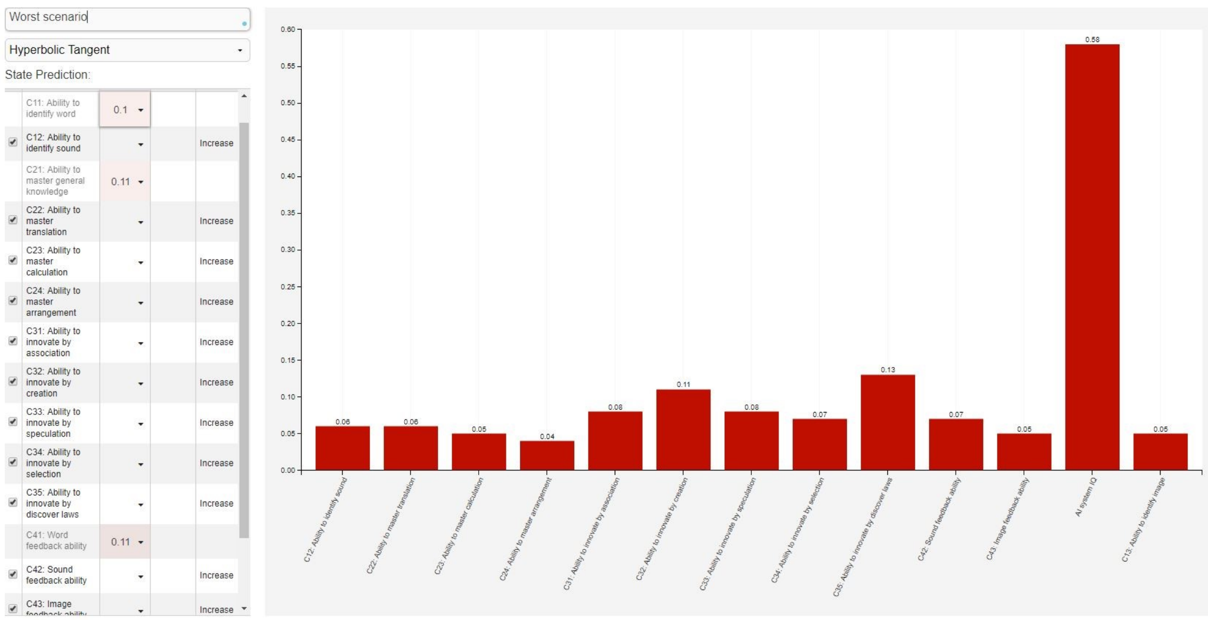

Figure 4: The driver concept effects for the worst scenario

FCM inference simulation

Based on the corresponding adjacency matrix (Table 5), there are some interrelations between concepts of this FCM. The value A_i of C_i is computed at each simulation step and it

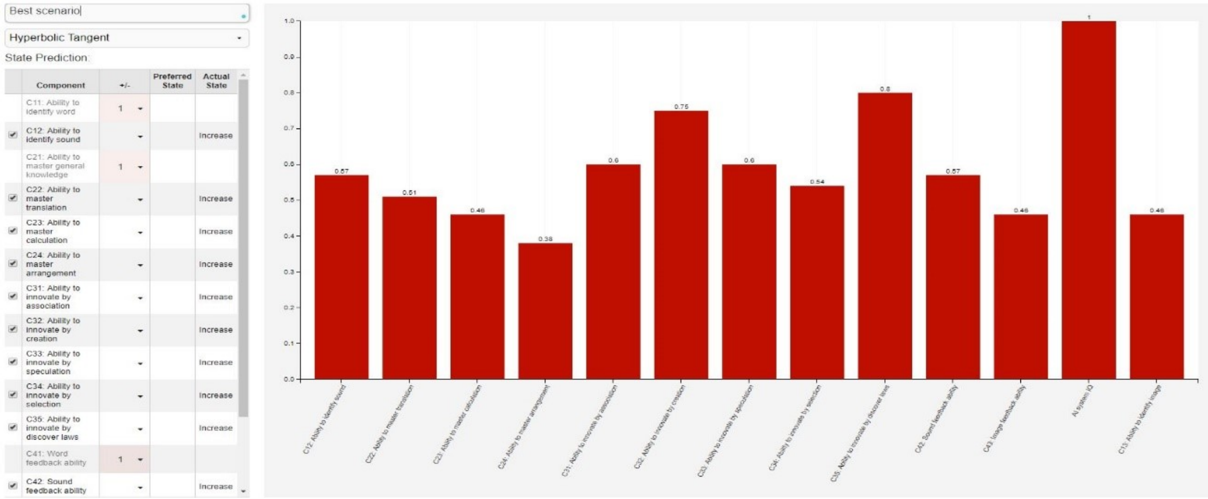

Figure 5: The driver concept effects for the best scenario

basically infers the influence of all other concepts C_j to C_i. This research selected Standard Kosko's activation rule inference method, below is the activation function:

$$A_t(K+1) = f\left\{\sum_{j=1, j\neq i}^{N} W_{ji} * A_j(k)\right\}$$

Also, the threshold function uses the sigmoid function, which shown as:

$$f(x) = \frac{1}{1+e^{-\lambda x}}$$

Where x is the value $A_i(K)$ at the equilibrium point, and λ is a real positive number ($\lambda > 0$) that determines the steepness of the continuous function f. Using sigmoid threshold ensure that the activation value belongs to the interval [0, 1].

When running the simulation, all the concepts were assigned an initial value of 0. After a few simulation steps, all the values were expected to be convergence status. Theoretically, after reaching the equilibrium end states, larger activation value means playing a more important role in this FCM. All the driver and ordinary concepts were used for the simulation task. Figure 6 shows the corresponding concept activation levels per each iteration with all 18 concepts ranging from 0 to 1. Table 8 gives us the inference concept values. All the inference simulations were run through "FCM Expert" software in this research.

Based on the plotter and the table results illustrated by the inference simulation process, it is easy to confirm that the top two critical roles are "C32: Ability to innovate by creation" and "C35: Ability to innovate by discover laws".

4 Summary and conclusion

In 2015, Liu *et al.* tested the selected 100 AI system based search engines IQ based on the Delphi weight approach [4]. This research article compares the new weight calculated through FCM approach to its original subjective approach and two other approaches while using the same data set as the input. Mean Square Error (MSE) is used here as a performance indicator,

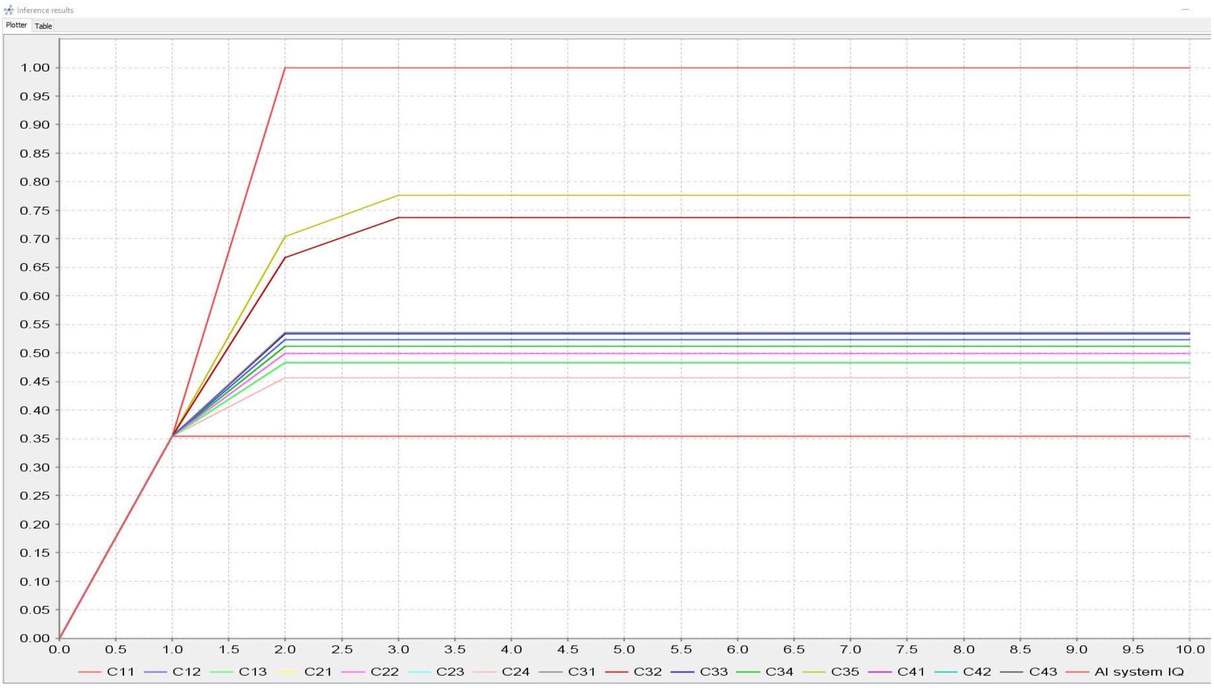

Figure 6: Simulation Activation level values per each iteration

Table 8: Inference concepts values

Step	C11	C12	C13	C21	C22	C23	C24	C31	C32	C33	C34	C35	C41	C42	C43	AI system IQ
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354
2	0.354	0.522	0.482	0.354	0.498	0.482	0.456	0.536	0.667	0.533	0.512	0.704	0.354	0.522	0.482	0.999
3-8	0.354	0.522	0.482	0.354	0.498	0.482	0.456	0.536	0.736	0.533	0.512	0.776	0.354	0.522	0.482	1
9	0.354	0.522	0.482	0.354	0.498	0.482	0.456	0.536	0.736	0.533	0.512	0.776	0.354	0.522	0.482	1
10	0.354	0.522	0.482	0.354	0.498	0.482	0.456	0.536	0.736	0.533	0.512	0.776	0.354	0.522	0.482	1

its equation can be found as below:

$$MSE = \frac{1}{N}\sum_{i}^{N}(y_i - \hat{y}_i)^2$$

Table 9 presents the MSE value for each approach. Dichotomous and polytomous [21] are two other old school methods. For the purpose of choosing the best approach, MSE works as a prediction error indicator here. It is to say, lowest MSE value means less prediction error. Based on MSE values, it is easy to say FCM approach is among the four approaches.

Table 9: MSE results for four methods

APPROACH	MSE
Delphi Weight	37.63363
Polytomous	49.51347
Dichotomous	31.23294
FCM approach	19.16389

This article presents a new method to assign weights for the edges of the FCM. The MSE criteria show the FCM approach has a better performance than the other three approaches.

According to the proposed FCM, it is easy to conclude that the AI system IQ score is not just determined by linear concept dependence combinations. Actually, it is a nonlinear one, because there are a few significant relationships between concepts.

The dynamic scenario analysis has shown that the driver concepts together have a significant positive impact on the AI system IQ and other related concepts. Due to the reference limitation, we didn't find sufficient negative relationships exist in this FCM.

Based on the inference simulation results, it is coherent to reveal that the higher importance of "C32: Ability to innovate by creation" and "C35: Ability to innovate by discover laws" and other concepts. The simulation after seven iterations illustrates that all the concepts adjusted to a convergence status, which means changing values of concepts, could affect but will be reaching an equilibrium end state.

There are also some limitations in the present study. Different literature resources may use different words, which are synonyms of the concepts. For example, some paper may use "verbal" to replace "sound". Another is the low quality of the original data. The original test result data set is highly distributed left. Which means the MSE performance indicator may have a bias. Also, there may be unidentified interrelationships between the concepts, which needs further literature investigation. Furthermore, This FCM used the methodology of fuzzy membership function and other techniques to capture the nature of the AI system IQ test, there is a lot of room for improvement in identifying the characteristics. For example, more sub-characteristics can be added into future FCM, even the most determined concepts affecting the AI system IQ score can be identified. Another thing that can be improved is the relationship between concepts, currently, most of the relationship edges are one-way directions, maybe some relationship can be a two-way direction. For example, AI system IQ may also have an impact to C23. After all the possible improvements, an advanced FCM dynamic scenario may be used to analyze and re-design the FCM to reduce some not significant edges.

Data availability

The data used in the research paper are available from the corresponding author upon request.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Funding statement

This research is supported in part by a grant from Chinese Academy of Sciences (#46-0806-0009). It is also supported by the Graduate Research and Creative Activity (GRACA) (#42-1209-9116) grant of the University of Nebraska at Omaha, and the grants of the National Science Foundation of China (No.7193000078, No.91546201).

Acknowledgment

We are using this opportunity to express our gratitude to Shihang Li and Joel McMaken from University of Nebraska at Omaha. We are thankful for their aspiring writing skill guidance, invaluable constructive advice during this research paper.

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