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Chronometric Constructive Cognitive Learning Evaluation Model: Measuring the Construction of the Human Cognition Schema of Psychology Students

Guadalupe Elizabeth Morales-Martinez and Janneth Trejo-Quintana
Cognitive Science Laboratory, IISUE,
National Autonomous University of Mexico, Mexico City, Mexico
https://orcid.org/0000-0002-4662-229X
https://orcid.org/0000-0002-7701-6938

David Jose Charles-Cavazos
TecMilenio University, Mexico City, Mexico
https://orcid.org/0000-0002-3445-9026

Yanko Norberto Mezquita-Hoyos
Autonomous University of Yucatán, Yucatan, Mexico
https://orcid.org/0000-0001-6305-7440

Miriam Sanchez-Monroy
Tecnologico Nacional de Mexico-Instituto Tecnologico de Merida, Yucatan, Mexico
https://orcid.org/0000-0001-5263-1216

Abstract. This study measured the structural and organizational changes in the knowledge schema of human cognition in response to the learning achieved by 48 students enrolled in the second year of a psychology degree. Two studies were carried out based on the Chronometric Constructive Cognitive Learning Evaluation Model. This article deals only with the first one, which consisted of a conceptual definition task designed in line with the Natural Semantic Network technique. Participants defined ten target concepts with verbs, nouns, or adjectives (definers), and then weighed the grade of the semantic relationship between the definers and the target concepts. The data indicate that the initial knowledge structures had been modified towards the end of the course. The participants' human cognition schema presented changes in terms of content, organization, and structure. This evidence supports the idea that the acquisition and transformation of the schemata learned in academic environments may be observed through cognitive science indicators.

Keywords: cognitive evaluation; knowledge schema; learning; NSN; psychology students

1. Introduction

Assessing academic learning is one of the most significant challenges for educators in the twenty-first century. This is supported by William (2011), who asserted that assessing learning is a central activity in the instruction-learning process. There is a great diversity of learning measurement tools, especially given the development of new technology, which has opened up new possibilities in this field. However, there is still no consensus on the most convenient way to assess student learning. This problem means that although there is a diversity of tools with which to measure academic learning, there is no agreement about the best way to determine what and how much content a student has learned during a course. El-Yassin (2015) remarked that there is no right or wrong way to evaluate student learning since each instrument can inspect a specific learning aspect. In addition, William (2011) pointed out that although the sequence of presentation, quality, and even teaching in a class is the same for all students, they understand what they learn in the classroom differently and may even learn different things to what they are taught.

This variability in students' academic learning has long been considered a barrier to teaching rather than a source of enrichment within the classroom. In this regard, William (2011) discussed how for many years, those involved in the educational field assumed that the quality of instruction alone would be enough for students to learn, and failure to learn in spite of effective instruction was attributed to the students' cognitive characteristics. Currently, the educational community is beginning to raise awareness about the role played by an individual student's needs and cognitive characteristics in the design of teaching-learning sequences.

Regarding the above, in the 1980s, Messick (1984) stressed that the interpretation of achievement measures should be carried out in the context of the style of instruction and learning to reduce errors in the interpretation of academic performance and students' functioning within specific learning environments. Although this proposal sounds obvious, Messick explained that measuring learning in such an all-encompassing way is rarely feasible due to the complexity of the information that needs to be extracted at different levels of student life.

In general, learning assessment can be very complex due to the broad spectrum of factors involved. According to Muskin (2015), the evaluation of learning implies using a means to determine what a person knows in conceptual or procedural terms. In this regard, Messick (1984) pointed out that school learning not only involves the content that a student can store in their memory, but also how the student structures or restructures their knowledge and cognitive skills according to their level of academic development (beginner, intermediate, or advanced).

Messick (1984) suggested that any learning measurement should take account of the state of academic development of each student to establish the cognitive functioning level at which the learning assessment will be carried out. For example, Messick proposed that with students in an initial learning phase, the objective should be to acquire information. At this level, information-retrieval recognition assessments could be used. In contrast, at a more advanced level, student learning should manifest itself in the restructuring of schemata and the flexible use of schemata to solve problems. However, Messick saw the application of such a proposal as very forward-looking rather than being based on the reality of developing performance tests.

Currently, most evaluation instruments are focused on performance measurement. In this regard, Banister (2004) pointed out that in psychology, the most commonly used instruments to measure learning are exams, practical tests, and empirical dissertations. These kinds of tools are used as summative assessments of student performance. The tests provide valuable information about aspects of students' knowledge of the information evaluated in the test. However, they are not planned to have implications for the design of instruction techniques (Arieli-Attali, 2013). Exams have been criticized for being indirect measures that do not take into account context and that are more oriented towards obtaining a product rather than understanding the learning process (Sadeghi & Rahmati, 2017).

Summative assessments are useful in this sense as they are used for what they were designed. However, when the main objective is to provide information on the processing of the information inputs that students receive in the classroom, rather than on the performance (the output from the process), then the necessary use of alternative tools to measure the cognitive processes of assimilation and accommodation of information as a result of learning becomes evident. Nevertheless, scientific exploration of the use and impact of evaluation tools to assess cognitive changes and provide useful indicators to correct or promote the restructuring of a learned schema is still an underexplored field.

One way to approximate this learning-evaluation challenge is to include cognitive psychology tools to measure the human mind. This scientific discipline has high potential to evaluate skills (Embretson, 1999) and the formation of knowledge structures, and can thus be applied to different aspects of the learning process. For example, Marzano's Learning Dimensions Model identifies five kinds of thinking involved in the learning process: a) attitudes and perceptions, b) acquisition and integration of knowledge, c) extending and refining knowledge, d) the meaningful use of knowledge, and e) mental habits (Marzano & Pickering, 1997). The measurement of these dimensions can be approximated with the paradigms and research techniques involved in human cognition science. For example, the research techniques used to explore human memory can be extrapolated to studying the cognitive mechanisms involved in dimensions b, c, and d of the Learning Dimensions Model.

Arieli-Attali (2013) stated that the idea of including advances in cognitive science to develop new forms of measurement or complement psychometric means of evaluation is not new. Initiatives have been emerging since the last century to link advances in cognitive psychology to the measurement of abilities. For example, the Air Force Human Resources Lab carried out the Learning Abilities Measurement Project (LAMP) (Kyllonen & Christal, 1988), which sought to identify indicators of student learning and achievement, taking into account measures for processing capacity, speed of processing, knowledge, and skills. The results of this seminal effort demonstrated that cognitive measures could successfully predict performance in learning tasks and even do so with greater precision than some instruments already available. Later initiatives such as the Cognitive Design System (CDS) (Embreston, 1999) or Evidence-centered Design (ECD) (Mislevy, Steinberg & Almond, 2003) have continued to promote the concept of using cognitive tools within the assessment of learning.

The Chronometric Constructive Cognitive Learning Evaluation Model (C3-LEM) by Lopez and Morales (Lopez et al., 2014; Morales-Martinez & Lopez-Ramirez, 2016; also see Morales-Martínez, 2020; Morales-Martinez et al., 2017; Morales-Martinez, Lopez-Ramirez & Lopez-Gonzalez, 2015) is a recent initiative to promote the use of cognitive measurement tools to evaluate academic learning. This evaluation model is based on applying the laws and principles for how the human mind selects, stores, and retrieves information.

From cognitive psychology, the human mind is seen as a producer of cognitive structures called schemata. These mental structures are formed with the knowledge that people store in their memories. Schemata possess properties relating to their flexibility and stability. In the educational field, the students form schemata from materials learned on a course or in a career. These schemata can remain or be modified over time, depending on how students store, organize and structure their learning.

Keeping the above idea in mind, Lopez (1989) proposed an academic-failure-rate predictor system based on evaluation techniques derived from the Theory of Human Information Processing (HIP) and the Theory of Parallel Distributed Processing (PDP). Lopez attempted to show that the study techniques from these areas allow the properties of learned-knowledge schemata to be observed and measured in the same way that general knowledge schemata can be observed. He tested this idea in his doctoral thesis, by designing and applying the Semantic Analyzer of Schemata Organization (SASO). This system allowed him to explore knowledge schemata in human memory (Lopez, 1996; Lopez & Theios, 1992). Later, Lopez et al. (2014) used this model to create a new system by which to evaluate learning. This learning-evaluation system was the origin of the Cognitive Evaluator (known in Spanish as EVCOG), which is a computerized system that assesses academic learning, and which gave rise to the C3-LEM developed by Morales-Martinez & Lopez-Ramirez (2016; also see Morales-Martinez et al. 2017, Morales-Martinez, Ángeles-Castellanos et al. 2020).

The C3-LEM (Figure 1) offers an alternative way to measure various aspects of mental representation of the knowledge students learn in academic courses. For example, this model allows indicators on the schematic organization of knowledge to be obtained. Arieli-Attali (2013) pointed out that measuring the conceptual understanding advances of students during a course can provide useful information to support the design of teaching and learning strategies that help students learn the knowledge and skills necessary to adapt to an environment whose economy is based precisely on information and knowledge management.

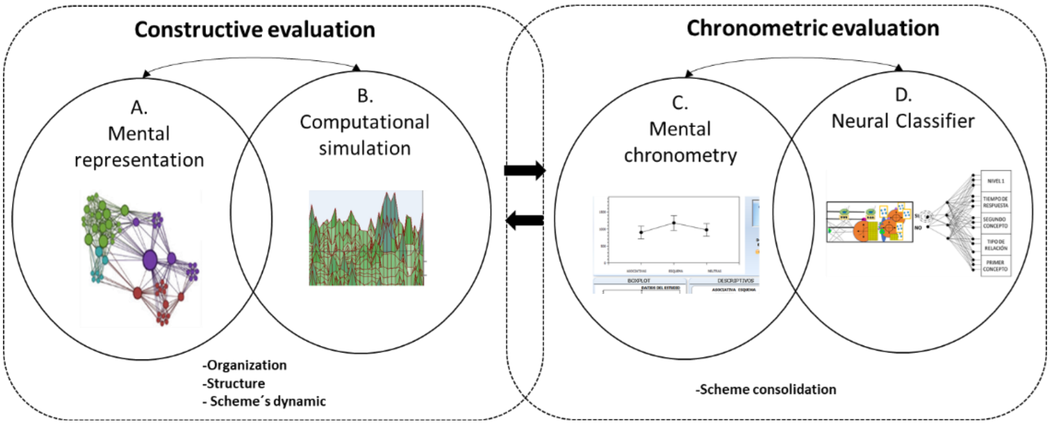


Figure 1. Phases and components of the C3-LEM
Note: From "Cognitive e-tools for diagnosing the state of medical knowledge in students enrolled for a second time in an anatomy course," by Morales-Martinez, Ángeles-Castellanos et al., 2020, *International Journal of Learning, Teaching and Educational Research*, *19*(9), p. 346 (https://doi.org/10.26803/ijlter.19.9.18). Copyright 2020 by the authors and IJLTER.ORG.

Figure 1. illustrates the phases and components that make up the C3-LEM. In general, this evaluation model promotes the combined and intertwined use of mental representation techniques, computational simulation tools, and chronometric cognitive measurement techniques to assess the modifications in the organization and mental structure of knowledge, as well as the dynamics and temporal changes in the learned schemata (Morales-Martinez, Ángeles-Castellanos et al., 2020; Morales-Martinez, Lopez-Perez et al., 2020).

C3-LEM studies are based on the EVCOG procedure, which consists of two phases: constructive cognitive evaluation and chronometric cognitive evaluation (Figure 1). Together, these two approaches provide indicators of students' cognitive mechanisms in terms of their ability to select, elaborate on, and build knowledge from the information obtained from an academic course. This article focuses on using the constructive cognitive evaluation of knowledge since it illustrates the first step for evaluating learning with C3-LEM. The objective is to contribute empirical evidence on the usefulness of cognitive techniques for measuring organization and structural changes in students' knowledge schemata due to the learning process in a human cognition course.

1.1. Constructive Cognitive Evaluation of Knowledge Schemata Learned during an Academic Course

The constructive cognitive evaluation of learning involves measuring the knowledge schema's properties through a mental representation technique and computer simulations. The central idea is to observe the conceptual changes that occur in the student's memory due to the learning process.

Typically, the first step consists of applying the Natural Semantic Network (NSN) technique at the beginning and the end of the academic year (see the Methodology section), although any other technique that allows organization indicators and conceptual structure to be extracted can be used. Figueroa, Gonzalez & Solis (1976) proposed the NSN as a mental representation technique to explore meaning formation. According to Figueroa-Nazuno (2007), the construction of meaning depends entirely on the person who constructs it. The person elaborates and interprets knowledge through a constructive and reconstructive process of memory. So, from this conceptualization of cognitive functioning, the formation of meaning goes beyond free association.

Mental representation studies based on the C3-LEM have provided evidence that students construct or reconstruct their declarative knowledge schemata as a result of the learning obtained during a course. For example, Morales-Martinez, Lopez-Perez et al. (2020) applied the NSN technique to measure the knowledge schema arising from a course on the Computational Theory of Mind. They observed that students enter the course with a pre-schema. However, no conceptual organization could be identified between the pre-schema nodes. After the course, the students had assimilated new concepts, eliminated some information nodes, and established an organization amongst the conceptual nodes they had learned during the course. These results agree with Bower's (1975) seminal idea that the acquisition of declarative schemata embraces the incorporation of new information nodes.

Moreover, the studies using NSN have been able to identify limitations in the knowledge structures of students, relating to each individual's level of academic development in terms of the subject they are learning. Morales-Martínez, Mezquita-Hoyos et al. (2018) noted that students who did not achieve passing grades on the computational usability course had fractured knowledge schemata at the end of the course. Morales-Martinez, Angeles-Castellanos et al. (2020) reported similar data in their cognitive diagnostic study on the structure and organization of the human anatomy knowledge schema amongst first-year medical students. The data from this study pointed to fractured cognitive structure in the schema and difficulties with conceptual organization.

Some reasons for schematic fragmentation include the relevance weight given to the different topics within a course or a lack of emphasis on establishing the relationships or connections between the topics reviewed during the academic course (Morales-Martinez, Ángeles-Castellanos et al., 2020). Fragmented knowledge structures are also observed in students starting a course to review a new topic (Morales-Martínez, López-Pérez et al., 2020; Urdiales-Ibarra et al., 2018).

Information integration strategies influence the formation or correction of integration limitations in knowledge structures such as those mentioned above. In this regard, Morales-Martínez, Mezquita-Hoyos et al. (2018) reported that engineering students with a fractured schema at the end of their course managed to integrate information from the computational usability schema after attending a corrective course on the subject.

In general, NSN provides information on how the student's mind organizes and structures knowledge schemata according to the learning experiences during academic courses. Few studies exist which have used the C3-LEM approach to explore the knowledge domain in psychology. Specifically, the topics covered to date using C3-LEM relate to the Piagetian Theory schema and the Computational Theory of Mind (e.g., Morales-Martínez, López-Pérez et al., 2020). The results of these studies suggested that students start the courses with vague but pre-organized ideas about the knowledge that they will review throughout the course. At the end of the course, students with passing grades had acquired new information nodes in the cognitive structures related to their knowledge. Additionally, they had established new relationships between concepts and reconstructed or reorganized their schemata based on their learning experiences. However, more investigations offering empirical evidence on the learning properties of knowledge schemata in psychology are necessary to build a solid theory about the behavior of schemata in this field of knowledge. The present study contributes new information on the organization and schematic behavior of the knowledge structures acquired in one of the most relevant fields of psychology science, human cognition.

2. Methodology

2.1. Study Overview

This research measured the state of knowledge on the human cognition schema amongst students enrolled in the second year of a psychology degree at the beginning and end of a course. The state of knowledge refers to the set of cognitive properties (organizational, structural, temporal, and dynamic) that characterizes students' knowledge schemata in any academic course. For example, at the beginning of a course, students present less semantic richness than at the end of the course. In addition, throughout the course, students judge the semantic relevance of concepts in different ways. Moreover, the recognition pattern for schematic words is different at the beginning, during, and at the end of the course. Thus, this study explored the changes in the organization and structure of the human cognition schema experienced by students as a result of the learning acquired during a cognition course. The authors designed an NSN study that included a conceptual definition task related to the human cognition schema.

2.2. Participants

The participants were 48 second-year psychology students enrolled in a course on human cognition. Their ages ranged from 19 to 34 years old (M = 20.3, SD = 2.58). Overall, 79% (38) were women and 21% (10) were men. The authors selected participants using a convenience sampling technique. Potential participants were included in the study only if they took part voluntarily and signed the informed consent. Participants who did not finish the two application phases or did not follow the instructions were excluded from the study.

2.3. Study Design

The study design was based on the EVCOG sequence proposed in the C3-LEM. The researchers designed a mental representation study based on the modified NSN from Lopez and Theios (1992) and Lopez (1996). The objective was to measure the cognitive properties of the content, organization, and structure of the human cognition schema.

2.4. Instruments and Materials

To build the NSN instrument, the researchers selected ten target concepts from the Protocol for the Collection of Target Concepts and Central and Deferred Definers (Morales-Martinez, 2015). This protocol guides the teacher or knowledge domain expert in terms of identifying the most relevant conceptual targets for the course. The resulting ten concepts were considered to be the evaluated schema concepts. The ten conceptual targets selected by the teacher were: cognition, cognitive psychology, perception, attention, consciousness, memory, representation of knowledge, reasoning, problem-solving, and decision-making.

The researchers used EVCOG software to design and apply the cognitive studies of mental representation. Additionally, this software allowed the capture and analysis of data based on the C3-LEM (Morales-Martínez, López-Pérez et al., 2020).

2.5. Procedure

In this study, the constructive cognitive evaluation of learning comprised the application of a task based on the NSN technique at the beginning and end of the course. First, the researchers invited students who were enrolled in a course on human cognition to participate in the research. Subsequently, the students who agreed to participate received information about the study and their rights as participants, and gave their informed consent. After this, they performed an exercise to familiarize themselves with the task. Finally, the NSN study was applied.

During the NSN study, each participant observed the target concepts one by one on a computer screen. The task was to define the targets using verbs, nouns, adjectives, and pronouns as definers. The production criterion for definers was that they had to be directly related to their course content on human cognition. Phrases, articles, and prepositions were not allowed to be used for the definitional task. The participants had 60 seconds to define each target. Subsequently, they rated each definer using a scale from 1 to 10; 1 meant that the evaluated definer chosen was not very related to the target concept, and 10 indicated that the definer was significantly related to the target concept. The time to complete the entire task varied from 15 to 20 minutes, depending on each participant.

3. Data Analysis

In this study, the authors undertook three analyses of the NSN data. The first analysis was a traditional mental representation analysis using the EVCOG system. This software allows several NSN values, proposed by Figueroa et al. (1976) and described by Lopez (1996) and Lopez and Theios (1992), to be computed. This analysis involved various elements which are described below. The indicators for the analysis included, firstly, semantic richness (J value), generated for each target concept through the total number of different definers. Secondly, semantic relevance (M value) was obtained from the score consciously given by the participants for each target definer, expressed as the sum of all the weights assigned by the participants to each definer. The ten most relevant defining concepts were also identified to build the meaning of the target concept of the network. This group of definers is known as the SAM group (Semantic analysis of M value or SAM) and is made up of the ten definers with the highest M values for each target concept. Another indicator was semantic distance (FMG value) between the given definer and the target concept that was defined. This is computed using the percentage range corresponding to the M value of each of the definers obtained for the SAM group in relation to the highest M value obtained in the group. Finally, semantic density (G value) was calculated.

The second analysis was undertaken using the EVCOG system. This software allowed the extraction of the association matrix. This matrix is called the SASO connectivity matrix, which is calculated using a Bayesian formula proposed by Lopez and Theios (1992). According to these authors, this equation is a modification of that by Rumelhart et al. (1986). Lopez and Theios's equation is given below:

$$W_{IJ} = -1n\{[p(X = 0 \& Y = 1)\ p(X = 1 \& Y = 0)]*[p(X = 1 \& Y = 1)\ p(X = 0 \& Y = 0)]^{-1}\} \quad [1]$$

This equation calculates the co-occurrence probability amongst pairs of concepts (X and Y) throughout the NSN. Firstly, $p(X = 0 \& Y = 1)$ refers to the joint probability that Y appears but X does not appear in a SAM group. Similarly, $p(X = 1 \& Y = 0)$ denotes the joint probability that X appears but Y does not appear in a SAM group, and $p(X = 1 \& Y = 1)$ was computed in the same manner. The calculation of $p(X = 1 \& Y = 1)$ involved the hierarchical modulation of M values in the SAM groups.

The SASO connectivity matrix was used to feed the Gephi software to obtain a graphical representation of the accommodation of schema concepts (see Figure 3). Finally, the authors used STATISTIC software (version 7) to apply a multidimensional scaling on the NSN data. To this end, the authors considered the co-occurrence of definer concepts for each target concept.

4. Findings/Results

4.1. Lopez and Theios's Analysis of NSN Data

The NSN data obtained before (Table 1) and after (Table 2) the course were analyzed based on the procedure described by Lopez and Theios (1992).

Table 1. SAM groups for the human cognition schema obtained from the participants before the course

Cognition				**Cognitive psychology**				**Perception**			
F	**Definer**	**M**	**IRT**	**F**	**Definer**	**M**	**IRT**	**F**	**Definer**	**M**	**IRT**
9	Cognitive process	158	18	9	Cognitive process	159	22	2	Senses	97	26
3	Mind	115	23	3	Mind	147	18	2	Interpret	67	35
5	Memory	110	27	5	Memory	141	36	2	Stimuli	63	23
3	Learning	88	32	5	Thought	93	26	9	Cognitive process	54	33
5	Thought	79	20	3	Learning	75	24	1	Feel	51	24
4	Attention	64	32	4	Attention	73	35	4	Attention	43	22
4	Perception	44	38	4	Perception	72	37	3	Brain	36	54
5	Capacity	40	41	1	Study	69	16	1	Observe	34	22
1	Processing	36	33	1	Behavior	64	29	4	Information	33	34
3	Brain	35	31	1	Science	47	18	1	Reality	26	41
	J-value: 218		**G-value** 12.30		**J-value:** 258		**G-value:**		**J-value:** 217		**G-value:** 7.10

Attention				**Consciousness**				**Memory**			
F	**Definer**	**M**	**IRT**	**F**	**Definer**	**M**	**IRT**	**F**	**Definer**	**M**	**IRT**
9	Cognitive process	129	24	3	Mind	78	23	1	STM	127	26
1	Focus	91	27	9	Cognitive process	55	30	1	LTM	105	29
5	Capacity	73	31	1	Mind state	45	11	1	Store	94	14
2	Stimuli	66	19	5	Thought	44	38	3	Learning	91	25
1	Concentrate	58	23	4	Attention	42	27	9	Cognitive process	88	28
5	Memory	38	24	3	Brain	40	44	1	Memories	86	24
2	Senses	36	38	1	Vigil	39	29	1	Remember	67	14
1	Selective attention	33	20	1	Internal	33	42	1	WM	65	30
4	Perception	31	47	2	Cognition	31	41	4	Information	63	32
2	Cognition	30	72	3	Reasoning	30	23	1	Retrieve	59	33
	J-value: 205		**G-value:** 9.90		**J-value:** 174		**G-value:** 4.80		**J-value:** 282		**G-value:** 6.80

Representation				**Reasoning**				**Problem solving**			
F	**Definer**	**M**	**IRT**	**F**	**Definer**	**M**	**IRT**	**F**	**Definer**	**M**	**IRT**
1	Schemata	95	22	3	Thinking	117	16	3	Reasoning	64	18
1	Image	81	20	9	Cognitive process	72	20	9	Cognitive process	56	28
1	Symbols	43	15	1	Human	47	22	3	Thinking	52	18
1	Models	39	21	5	Thought	46	25	2	Reason	51	16
1	Mental	36	15	3	Analysis	45	33	5	Memory	46	27
4	Perception	33	32	1	Logic	43	19	5	Capacity	44	19
4	Information	31	31	1	Consciousness	32	33	3	Analysis	41	28
1	Object	28	27	5	Capacity/Ability	31	27	2	Choice	39	36
5	Memory	27	39	4	Information	29	30	2	Options	38	41
1	Concepts	27	37	2	Interpretation	27	46	5	Thought	38	32
	J-value: 175		**G-value:** 6.80		**J-value:** 200		**G-value:** 9.00		**J-value:** 192		**G-value:** 2.60

Decision making			
F	**Definer**	**M**	**IRT**
2	Choice	104	17
9	Cognitive process	73	34
2	Options	58	30
1	Evaluation	53	39
2	To reason	42	18
1	Solutions	38	31
5	Capacity	34	33
3	Reasoning	33	26
3	Analysis	31	40
3	Thinking	27	50
	J-value: 212		**G-value:** 4.60

Note: J = semantic richness, G = semantic density, F = occurrence frequency, M = semantic weight, IRT = inter-response time

Table 2. SAM groups for the human cognition schema obtained from the participants after the course

Cognition				Cognitive psychology				Perception			
F	**Definer**	**M**	**IRT**	**F**	**Definer**	**M**	**IRT**	**F**	**Definer**	**M**	**IRT**
10	Cognitive process	259	13	10	Cognitive process	230	26	1	Sensation	182	13
3	Information	98	28	1	Science	167	20	1	Interpret	152	22
2	Mind	89	22	1	Neisser	113	23	1	Threshold	125	29
7	Memory	80	33	2	Cognition	92	30	2	Stimuli	116	27
1	Cold cognition	79	31	7	Memory	79	31	10	Cognitive process	110	32
3	Attention	68	33	1	HIP	78	29	1	Direct perception	84	26
1	Psychology	63	43	3	Information	76	31	1	Illusion	69	30
1	Hot cognition	54	29	1	Representation	63	41	1	Senses	62	24
1	Human	49	42	3	Attention	62	36	4	Perception	55	24
1	Processing	49	32	4	Perception	61	32	1	Gestalt	49	44
	J-value: 373	**G-value:** 21.00			**J-value:** 378	**G-value:** 16.90			**J-value:** 336	**G-value:** 13.30	

Attention				Consciousness				Memory			
F	**Definer**	**M**	**IRT**	**F**	**Definer**	**M**	**IRT**	**F**	**Definer**	**M**	**IRT**
1	Filter	211	22	3	Attention	134	25	1	Store	286	20
10	Cognitive process	190	20	10	Cognitive process	127	24	1	Retrieve	258	30
1	Selective attention	124	23	1	Become aware	94	17	1	LTM	232	32
1	Divided attention	95	31	7	Memory	83	35	1	STM	231	27
2	Stimuli	93	39	4	Perception	67	36	1	SM	230	26
1	Attenuation model	82	25	2	Knowledge	62	11	1	Encoding	147	29
1	Sustained attention	81	23	1	Unconscious	49	43	10	Cognitive process	112	22
1	Capacity	78	28	1	Explicit	48	42	1	WM	96	34
4	Perception	71	25	1	Reflector	41	36	1	Implicit	77	25
1	Focus	68	28	2	Cognition	41	49	2	Semantics	74	41
	J-value: 360	**G-value:** 14.30			**J-value:** 279	**G-value:** 9.30			**J-value:** 411	**G-value:** 21.20	

Representation				Reasoning				Problem solving			
F	**Definer**	**M**	**IRT**	**F**	**Definer**	**M**	**IRT**	**F**	**Definer**	**M**	**IRT**
1	Schemata	261	23	1	Reasoning	239	20	1	Objective	114	30
2	Mind	198	19	1	Conclusion	216	25	10	Cognitive process	103	19
1	Concepts	142	26	1	Inductive	201	20	1	Problem	100	25
10	Cognitive process	99	25	1	Syllogism	175	26	2	Reasoning	87	30
7	Memory	98	33	1	Analogical	110	27	1	Goal	81	17
1	Images	74	20	10	Cognitive process	109	23	1	Heuristics	77	37
1	Imagine	73	14	1	Premises	86	24	7	Memory	76	48
2	Knowledge	59	24	3	Information	78	25	2	Decision	70	38
2	Semantics	43	42	7	Memory	66	34	1	Strategies	56	33
1	Absence	41	18	1	Logic	60	26	1	Initial state	55	29
	J-value: 332	**G-value:** 22.00			**J-value:** 344	**G-value:** 17.90			**J-value:** 311	**G-value:** 5.90	

Decision making			
F	**Definer**	**M**	**IRT**
1	Choice	222	14
1	Alternative	112	19
10	Cognitive process	105	29
1	Evaluation	94	19
1	Experience	80	25
2	Reasoning	79	37
2	Decision	78	18
1	Options	62	29
7	Memory	56	32
1	Normative theories	23	35
	J-value: 331	**G-value:** 5.90	

Note: J = semantic richness, G = semantic density, F = occurrence frequency, M = semantic weight, IRT = inter-response time

Table 1 shows that the definers (*cognitive process, mind, memory, short-term memory (STM), thinking, long-term memory (LTM), choice, senses, schemata*) with the highest M in each SAM group before the course were mostly general. At the end of the course, however, most of the concepts with the highest

M in each SAM group were specific (*cognitive process*, *sensation*, *filter*, *attention*, *store*, *schema*, *reasoning*, *objective*, *choice*), as shown in Table 2. Besides, when comparing Tables 1 and 2, it can be observed that the students at the end of the course included new definers or information nodes, rearranged some definers, or eliminated concepts in the definitions of some targets. For example, the following definers for *cognition*: *thought*, *capacity*, *perception*, *learning* and *brain* were removed, and definers such as *information*, *cold cognition*, *psychology*, *hot cognition*, and *human* were included (Figure 2).

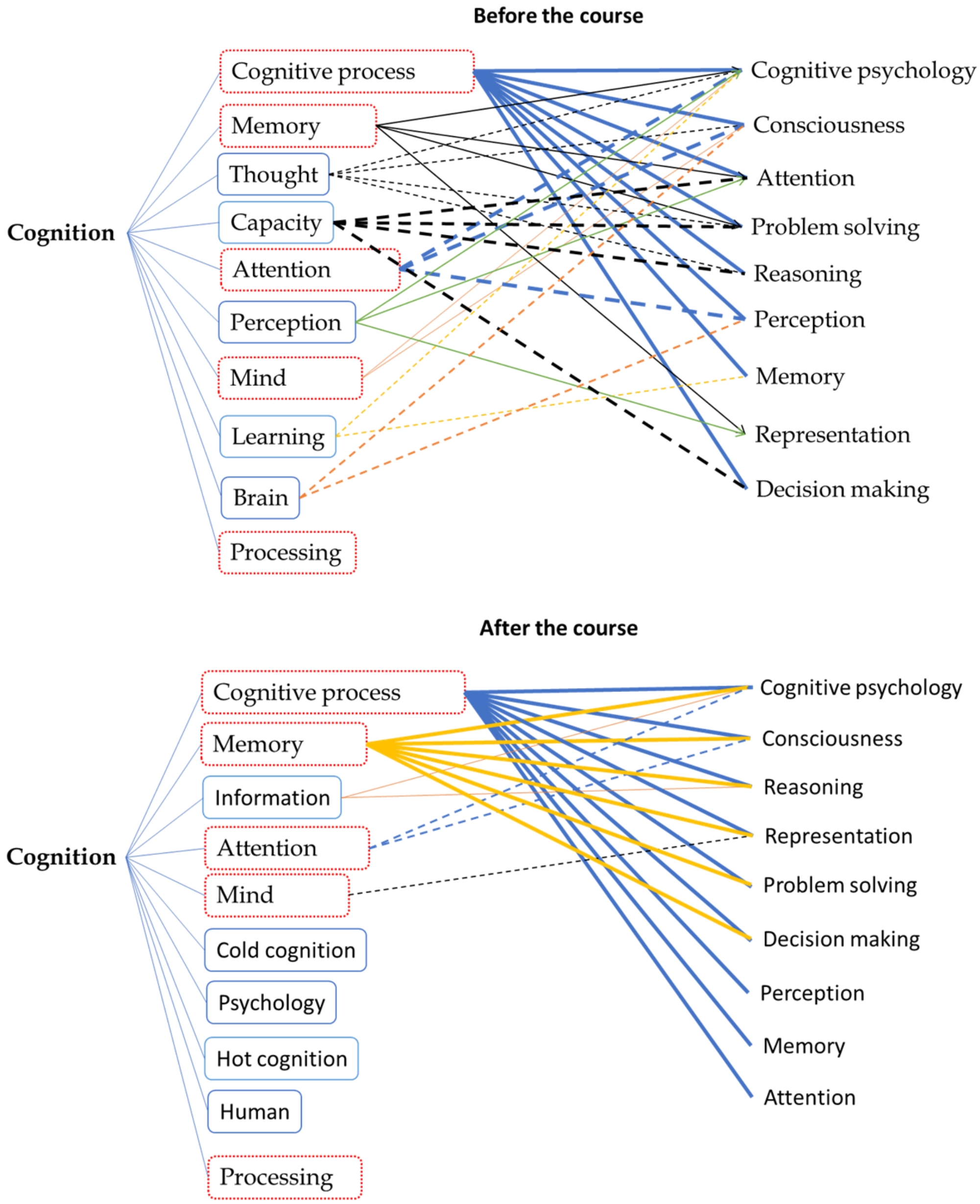


Figure 2. Conceptual changes in the target *cognition*

In general terms, *cognitive process* (M value = 159) was the definer with the greatest semantic weight in the entire network before the course (Table 1), whilst after the course, it was *store* (M value = 286) (Table 2). Additionally, *cognitive process* was the definition with the highest appearance frequency at the beginning of the course (F = 9) and also at the end of the course (F = 10). The M value average for *cognitive process* at the beginning of the course was 93.77, whereas at the end of the course, it had increased to 144.4.

4.2. Gephi Analysis of NSN Data

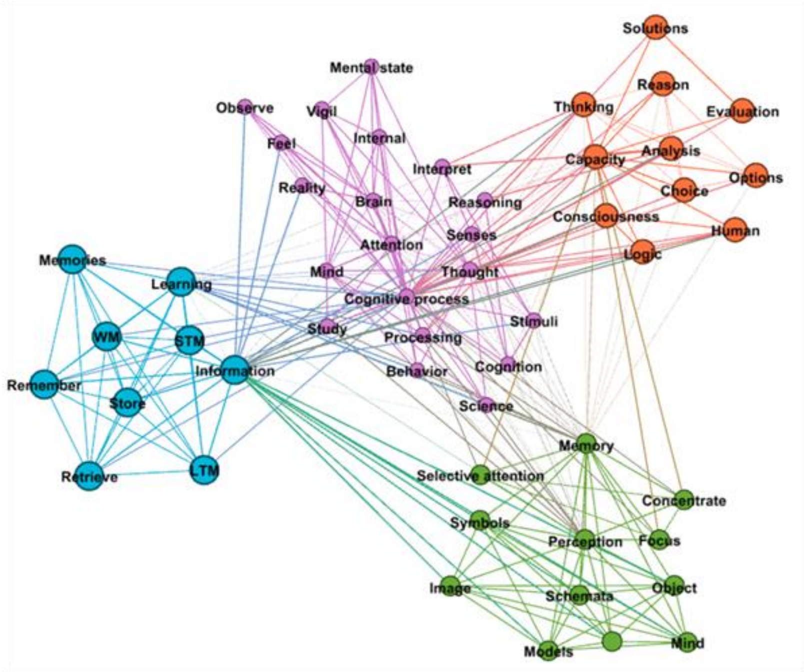
The researchers carried out a graphical analysis of the changes in the organization and structure of the NSN using the Gephi system (Bastian, Heymann & Jacomy, 2009). Gephi is open-access software which explores the properties of networks.

At the beginning of the course, the participants' knowledge schema on human cognition was made up of four large modules of concepts (Figure 3). The first (blue) included memory-related definers (*memories*, *learning*, *remembering*, *storing*, *retrieval*, *working memory (WM)*, *short-term memory*, *long-term memory*, *information*). The second group (purple) consisted of definers related to cognitive psychology as a science (*science*, *study*, *cognition*, *mental state*, *observing*, *wakefulness*, *feeling*, *internal*, *reality*, *interpretation*, *reasoning*, *attention*, *senses*, *mind*, *thought*, *cognitive process*, *stimuli*, *processing*, *brain*, *behavior*). The third grouping (orange) embraced definers related to decision-making (*solutions*, *reasoning*, *thinking*, *evaluation*, *analysis*, *ability*, *options*, *choice*, *consciousness*, *human*, *logic*). The fourth group of definers (green) was made up of concepts relating to cognitive processes (*memory*, *selective attention*, *concentration*, *symbols*, *perception*, *focus*, *image*, *schemata*, *models*, *mind*).

After the course, the participants rearranged the human cognition schema into seven conceptual modules (Figure 3). The first module embraced definers associated with perception (orange) (*senses*, *interpretation*, *illusion*, *sensation*, *threshold*, *direct perception*, *Gestalt*). The second module (light green) included definers related to consciousness and attention (*sustained attention*, *divided attention*, *selective attention*, *capacity*, *attenuation model, unconscious*, *filter*, *focus*, *realize*, *reflector*, *explicit*). Module 3 (pink) grouped concepts related to problem-solving (*initial state, strategies, problem*, *goal*, *heuristics*, *objective*). Conceptual group 4 (dark green) encompassed definers on decision-making (*alternative*, *options*, *choice*, *evaluation*, *experience*). Module 5 (purple) concentrated concepts related to three objectives: cognitive psychology, cognition, and mental representation (*schemata*, *images*, *absence*, *concepts*, *cold cognition*, *imagine*, *mind, processing, hot cognition, human, reasoning, cognition, stimuli, decision, semantics, memory, psychology, memory, Neisser, cognitive process, mental representation, HIP, science, attention, knowledge*). Module 6 (brown) included definers on reasoning (*deductive reasoning*, *premises*, *conclusion*, *logic*, *inductive*, *analogical*, *information*, *syllogism*). The last module (blue) involved definers related to memory (*sensory memory*, *short-term memory, long-term memory, retrieve, store, encoding, working memory*, *implicit*).

Additionally, the Gephi analysis pointed out changes in the conceptual organization. The conceptual connections of definers had changed at the end of the course. To illustrate these changes, observe in Figure 3 that at the beginning of the course, c*ognitive process* was a central definer concept in the primary schema that participants brought about human cognition, although it did not have a connection with all the schema modules. At the end of the course, the concept of *cognitive process* retained its quality as a central conceptual node yet now also fully connected with all the targets and all the conceptual modules.

Before the course



After the course

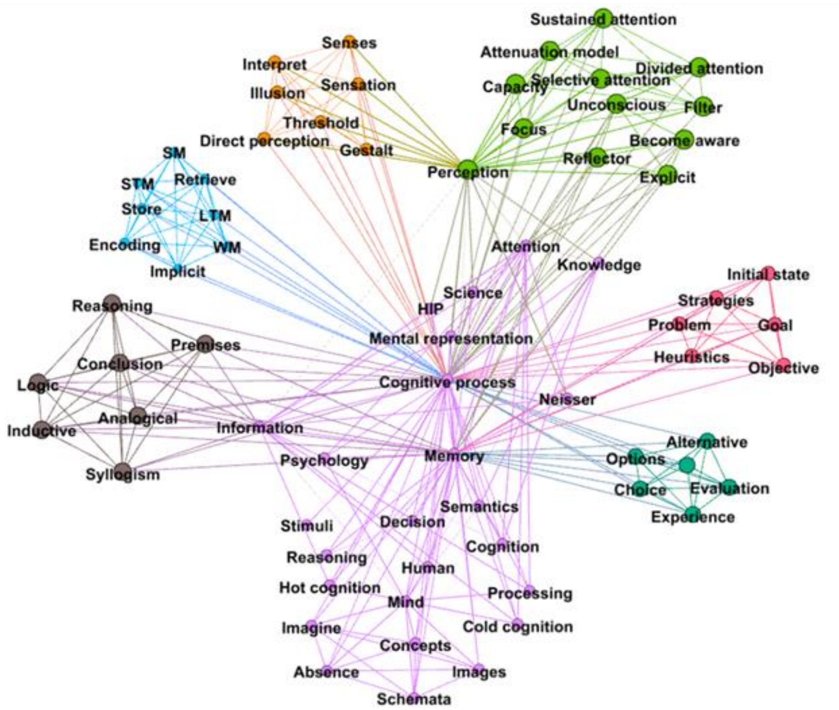


Figure 3. Gephi analysis of the NSN data obtained before and after the course

4.3. Multidimensional Scaling of NSN Data

The researchers applied multidimensional scaling to the NSN data to examine the general structure of the human cognition schema. The analysis showed changes in the arrangement of target conceptual nodes due to the learning achieved during the course (Figure 4).

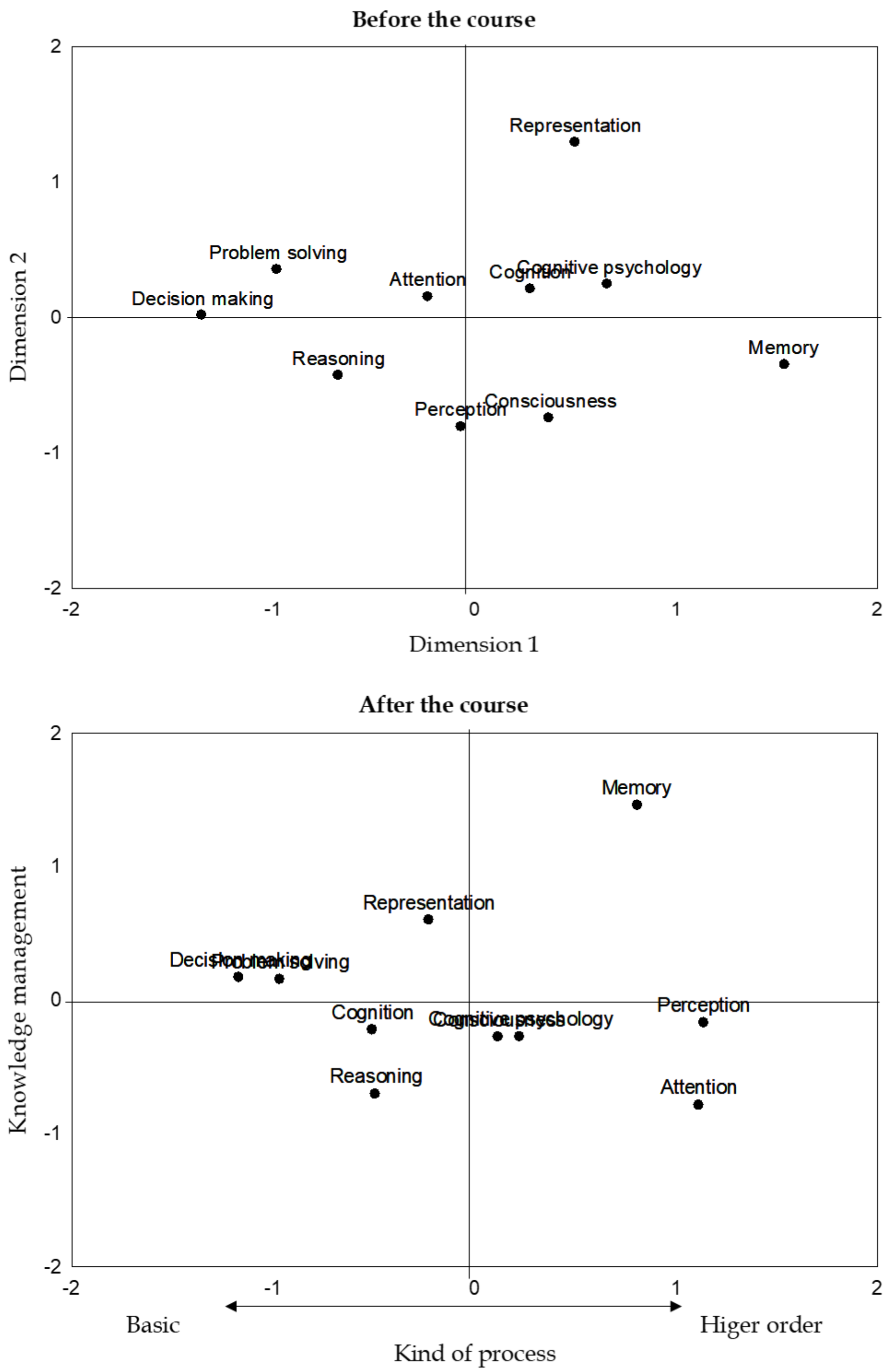


Figure 4. Multidimensional scaling analysis of the target concepts

The multidimensional scaling graph shows that the participants started the course without a specific structure in mind for the objective concepts, whilst at the end of the course, they had rearranged the objective concepts based on two dimensions. The first related to categorizing cognitive processes in terms of basic and higher order cognition (horizontal axis). Although the definition of the second dimension is not clear, in general, this dimension seems to be related to the use of knowledge structures (vertical axis). Note that the target concept for *reasoning* does not appear alongside targets such as *problem-solving* or *decision-making*, even though all of these processes involve making use of knowledge structures from memory.

5. Discussion

This study has explored changes in the knowledge schema due to the learning process during a course on human cognition taken by second-year psychology students. First, the authors determined whether a human cognition schema existed before the course. The NSN and Gephi analyses indicated that the participants entered the course with a previous-knowledge schema or a knowledge pre-schema (see Table 1 and Figure 3). The existence of a knowledge pre-schema has been observed in other studies (e.g., Morales-Martinez, Lopez-Perez et al., 2020); however, the organization and structure are rudimentary. This finding suggests that students generally have a vague schema about the knowledge they will acquire in their courses, and it is based on this schema that they reorganize and reconfigure the information they will learn in class.

As psychology teachers, the authors have observed that the use of general schemata and previous learning to begin a new knowledge schema is a common phenomenon observed in the classroom. Students generally comment that they have come across certain information about the topic. It was therefore not unexpected that the participants in this study commented that they were slightly familiar with the topics. They had reviewed readings on cognitive processes in other courses, although this had not been from the perspective of the field of cognitive psychology.

The authors hypothesize that students use their previous learning experiences to form a general schema or make inferences about information related to the course in which they are enrolled. In this way, they have a conceptual basis from which to form a more sophisticated outline of the information they cover during the course. From a cognitive perspective, students can use or create a rudimentary cognitive structure that allows them to guide the reorganization and restructuring of their knowledge based on the new information inputs that they acquire through the course. If the cognitive structure is sufficiently broad and general, it will be flexible enough to undergo modifications due to the new learning experiences.

Interestingly, although the initial schema with which the participants in this study entered the course was very general, their schema was not fractured as has been observed in other courses where students start on a topic for the first time (e.g., Urdiales-Ibarra et al., 2018). This result may be because the participants in this study had reviewed cognition materials the previous year when taking different courses, meaning that they had had previous information about the topic. At the start of their degree, the participating students were enrolled in a course where they reviewed some of the concepts included in the course on human cognition and obtained a passing grade on this initial course. Thus, they had general and pre-organized ideas about the meaning of some important target concepts in NSN studied in this research. Other studies have indicated that students who do not obtain a passing grade for a course have a fragmented schema at the end of the course compared to those who end the course with a passing grade (Morales-Martinez, Angeles-Castellanos et al., 2020; Morales-Martinez, Mezquita-Hoyos et al., 2018).

In this study, at the end of the course, the authors explored the changes that had taken place in the participants' pre-knowledge schema of human cognition due to the learning acquired through the course. The analysis of the organization of the schematic knowledge indicated that the participants had established new relationships between the concepts. This result is consistent with Bower's (1975) idea that the acquisition of declarative schemata necessarily involves incorporating new information nodes and new connections between these nodes.

The reader can compare the definers included in Tables 1 and 2 and observe that at the beginning of the course, for some target concepts, some of the definers were global concepts on the topic of human cognition. Meanwhile, at the end of the course, the definers were more specific and theoretically closer to the target evaluated. For example, for the initial conceptual definition of human cognition (Figure 2), half of the concepts were categorical (*memory*, *thought*, *attention*, *perception*, *learning*), and the other half were schematic (*cognitive process*, *capacity*, *mind*, *brain*, *processing*). At the end of the course, however, the participants included a greater number of schematic-type definers (*cognitive process*, *information*, *mind*, *cold cognition*, *psychology*, *hot cognition*, *human*, *processing*).

The change in predominance from categorical to schematic relationships in knowledge structures suggests that the participants had developed more sophisticated schemata. That is, instead of using as many exemplification schemata, their perception had changed and they were using more probabilistic schemata. It is possible that, when students start learning a knowledge domain, learning by exemplification dominates most of their knowledge acquisition process. As participants in this study acquired new knowledge and refined it, they began to use or establish other semantic relationships amongst the concepts. It would be useful to carry out further research to explore this phenomenon since there has been no discussion of this issue in previous research with C3-LEM to date (e.g., Morales-Martinez, Angeles-Castellanos et al., 2020; Morales-Martinez et al., 2020; Morales-Martínez, Mezquita-Hoyos et al., 2018; Urdiales-Ibarra et al., 2018).

Another modification in the knowledge organization, which is of note, was the change in the degree of generality with regard to the human cognition schema. At the beginning of the course, the participants formed some groups that included general definers and even incorporated information from other knowledge schemata. For instance, module 2 of the Gephi analysis shows that before the course, participants included definitions of various target concepts (*cognitive psychology*, *cognition*, *mental representation*, *perception*) in the same group of concepts and included definitions of other knowledge schemata learned for other topics. For example, participants recovered conceptual nodes from the behaviorism field as *stimuli* instead of *inputs* or *behavior* instead of *cognitive patterns* (Figure 3).

The previous results indicate that at the end of the course, the participants were able to extend and refine their knowledge about human cognition, thus placing them at level three of Marzano's Dimensions of Learning Model (Marzano & Pickering, 1997). On the other hand, according to Messick (1984), the participants in the present study would be in an intermediate stage of academic development in terms of the development of the knowledge schema on human cognition because indicators observed included not just the retrieval of information but a restructuring of their schema. In congruence with this idea, the analysis of the structural changes in the knowledge schema indicated a reconfiguration of the schema structure by the end of the course. In this regard, Figure 3 shows how the initial schema's definers were arranged into four large modules, whilst the definers for the final schema were restructured into seven conceptual modules.

Changes in the configuration of the schematic structure have been observed in other studies that have used the C3-LEM (Morales-Martinez, Lopez-Perez et al., 2020; Morales-Martínez, Mezquita-Hoyos et al., 2018; Urdiales-Ibarra et al., 2018). From the point of view of cognitive psychology, changes in schematic configuration patterns are an indication of learning. In this study, the changes to the schema's configurational arrangement suggest that participants had rebuilt their structures based on the new meanings that they had acquired during the course.

The multidimensional analysis (Figure 4) on the target concepts showed that at the beginning of the course, the participants did not have a clear idea of how the course's target concepts could form a wholly organized knowledge schema. At the end of the course, the participants organized the ten target concepts into two dimensions, the first one relating to the cognitive nature of the processes (basic vs. higher order cognition) and the second associated with the use of knowledge structures. Although some concepts such as *reasoning* were not correctly located in this second dimension, in general terms, this result suggests that the participants had understood the structure of knowledge underlying the course's thematic organization, using the information implicit in the same target concepts. Since this is a seminal intent of introducing a new way to analyze the results from C3-LEM, more evidence about this phenomenon is needed to explore and explain this kind of implicit cognitive change in the knowledge schema as a learning product.

In summary, the study results indicated that there were changes in the organization and structure of the human cognition knowledge schema of the participants. They had reconfigured their old four-module schema on human cognition into a new one which included seven modules. The participants included new information nodes, eliminated conceptual nodes that belonged to other disciplines, and established new relationships between the old and new concepts.

6. Conclusions

In conclusion, the results of the present investigation have implications in three areas. At a theoretical level, the study generated empirical evidence that supports the idea that students enter courses with prior knowledge of the subject they are going to study. For example, the study data indicated that the participants possessed a macro-schema of human cognition at the beginning of the course. This finding is relevant because it suggests that cognitive techniques such as those contemplated in the C3-LEM can help diagnose preconceived ideas. It opens up the possibility of correcting inaccurate information held by students when starting a course. The measurement of this type of pre-schema would empower the teacher to decide whether it is necessary to demystify some information or whether modifications are required in the application of the established work program to provide continuity or correct the knowledge structures held by students when starting the course.

In addition, the results demonstrated that the learning process involves the assimilation of new information and the elimination of specific conceptual nodes, as well as the restructuring of schematic information. Furthermore, evidence from the NSN study indicated that this type of technique can provide information on students' academic development level in a course. This finding has important implications at the applied level. For example, how a student configures their knowledge can also be taken as an indicator of mastery of the course knowledge. Consequently, the C3-LEM could be a valuable tool in the formative assessment of students. However, since the sample in this study was small and only addressed one domain of knowledge, new explorations must be carried out in other fields, such as the area of exact sciences (e.g., mathematics, chemistry, physics), to calibrate the scope and implications of this evaluation model in the design of new forms of educational evaluation and intervention.

Finally, at a methodological level, the study's data supported the idea that mental representation studies from the C3-LEM perspective may help assess cognitive changes in the organization and structure of knowledge schemata.

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