



European Journal of Educational Research

Volume 12, Issue 2, 837 - 850.

ISSN: 2165-8714

<https://www.eu-jer.com/>

Constructive Cognitive Assessment of Learning in a Course on the Computational Cognition in Psychology Students

Guadalupe Elizabeth

Morales-Martinez* 

National Autonomous University of
Mexico (UNAM), MEXICO

Angel Garcia-Collantes 

Distance University of Madrid (UDIMA),
SPAIN

Rafael Manuel Lopez-Perez 

Fundación Universitaria Behavior & Law,
SPAIN

Received: October 31, 2022 • Revised: January 9, 2023 • Accepted: March 13, 2023

Abstract: Learning evaluation is a complex task, and this study illustrates the Constructive Assessment of Learning as a complementary alternative to evaluate the computational cognition schema construction. The authors designed a mental representational task under the Chronometric Constructive Cognitive Learning Evaluation Model. Control and experimental groups performed a conceptual definition task based on the Natural Semantic Network technique (NSN). They defined ten target concepts related to computational cognition theory, using verbs, nouns, and adjectives as definers. Afterward, the participants rated the conceptual quality of each definer one by one, on a scale of one to ten; the higher the rating, the greater the quality of the definer to define the target concept. The results indicate that the NSN technique was sensitive to measuring and discriminating cognitive changes in knowledge structures produced by the specific learning of computational cognition theory. In contrast, the learning of broad psychology subjects produced general cognitive changes without organization related to the specific learning of the evaluated course. Data showed more sophisticated cognitive change patterns on the evaluated schema in the experimental group than in the control group. The findings of this study suggest that cognitive assessment techniques can be helpful in the formative assessment of learning and provide clear indicators of students' knowledge management skills.

Keywords: *Academic learning, cognitive evaluation, mental representation of knowledge, natural semantic networks.*

To cite this article: Morales-Martinez, G. E., Garcia-Collantes, A., & Lopez-Perez, R. M. (2023). Constructive cognitive assessment of learning in a course on the computational cognition in psychology students. *European Journal of Educational Research, 12*(2), 837-850. <https://doi.org/10.12973/eu-jer.12.2.837>

Introduction

Incorporating technological advances into the educational field and the emergence of a new vision of learning and teaching transformed student and teacher roles in face-to-face and digital school environments. The student's mind is no longer seen as a mere receiver of knowledge but actively participates in learning. On the other hand, the teachers' task goes beyond transmitting information; now, they are facilitators of learning experiences considering the students' characteristics, interests, and motivations. Moreover, the teacher encourages students to learn knowledge management skills. In short, learning and teaching went from a linear vision to a conception of co-construction of knowledge.

Educational technology innovations reflect this conceptual change in learning and teaching. For example, in digital instruction, educational platforms stimulate self-regulated learning. The digital, interactive, and immersive didactic resources help students to immerse themselves in interesting and challenging activities. Asynchronous and synchronous communication tools used between students and teachers promote independent time-management. These and other developments in digital instruction provide new opportunities to learn and teach throughout the 21st century vision. In contrast to the advances in instruction, learning evaluation presents a gap in integrating new technologies and advances in learning science to develop alternative means of evaluation that align with the needs of the 21st century classroom. Morales-Martinez (2020) mentioned that most current evaluation instruments in digital education are technological encapsulations of the tools of knowledge evaluation that have long been used in face-to-face teaching.

On the other hand, no instruments measure all aspects of learning (El-Yassin, 2015). Furthermore, instruments that provide numerical indicators currently predominate. In this regard, Conway et al. (1992) pointed out that numerical indicators do not necessarily reflect the ability to retain knowledge in the long term. In addition, instruments such as tests, provide little information to discriminate between successful strategies unrelated to learning and the acquisition

* Corresponding author:

Guadalupe Elizabeth Morales-Martinez, National Autonomous University of Mexico (UNAM), Mexico. ✉ gemoramar@hotmail.com

level of long-term cognitive skills (Marzano, 1994). Thus, one of the most relevant challenges of education in the 21st century is to expand towards an evaluation of learning that includes indicators measuring the new cognitive demands associated with the information age.

Only a limited number of evaluation alternatives incorporate the modern vision of learning, new technologies, and advances in science learning. Since the cognitive theoretical approach focuses on the cognitive principles and laws that govern the functioning of the human mind, it can be applied to deepen our understanding of both students' and teachers' minds while learning and teaching academic knowledge. This study aims to assimilate and take advantage of some cognitive psychology developments to contribute to the innovation of learning assessment instruments by using cognitive assessment techniques that are compatible with new technologies that would allow the creation of novel digital methods of learning assessment to systematically observe the development of cognitive skills such as the integration, organization, and management of learned knowledge.

Arieli-Attali (2013) pointed out that measuring these information-processing skills during academic learning is central to training 21st-century students since they are immersed in a society whose economy revolves around information management. One way to approximate the evaluation of the cognitive management of learned knowledge is by using cognitive tools that explore two fundamental aspects of learning: the process and the result. The process includes the evaluation of the cognitive processing mechanisms and the content or information that the student selects, receives, and stores. The result refers to the evaluation of the direct and unobservable manifestations of learning (e.g., cognitive changes in the schema) or the visible response (e.g., motor changes) of the same (Morales-Martinez, Hedlefs-Aguilar et al., 2021). Here, the changes in the student's cognitive structures due to learning through interaction with their academic environment are particularly interesting (Moreno, 2010).

The cognitive sciences' theoretical, experimental, and mental representation paradigms help measure the cognitive changes due to academic learning. In this regard, the Chronometric Constructive Cognitive Learning Evaluation Model (C3-LEM) (Lopez-Ramirez et al., 2014; Morales-Martinez, 2020; Morales-Martinez et al., 2015, 2017; Morales-Martinez & Lopez-Ramirez, 2016), is a functional cognitive approach for assessing the cognitive changes produced by learning in the student's minds. This cognitive learning evaluation model works under human serial and parallel information processing principles. It provides cognitive tools to explore and explain how students' minds work when forming knowledge structures.

The C3-LEM comprises two phases (Figure 1); the first is the constructive cognitive evaluation of learning, in which mental representation techniques and computer simulation allow for identifying the organizational, structural, and dynamic properties of the evaluated knowledge cognitive schema. The second phase (chronometric cognitive evaluation of learning) measures the degree of knowledge consolidation in the student's memory. Here, the researchers observe the temporal patterns of the evaluated knowledge schemas through chronometric cognitive techniques.

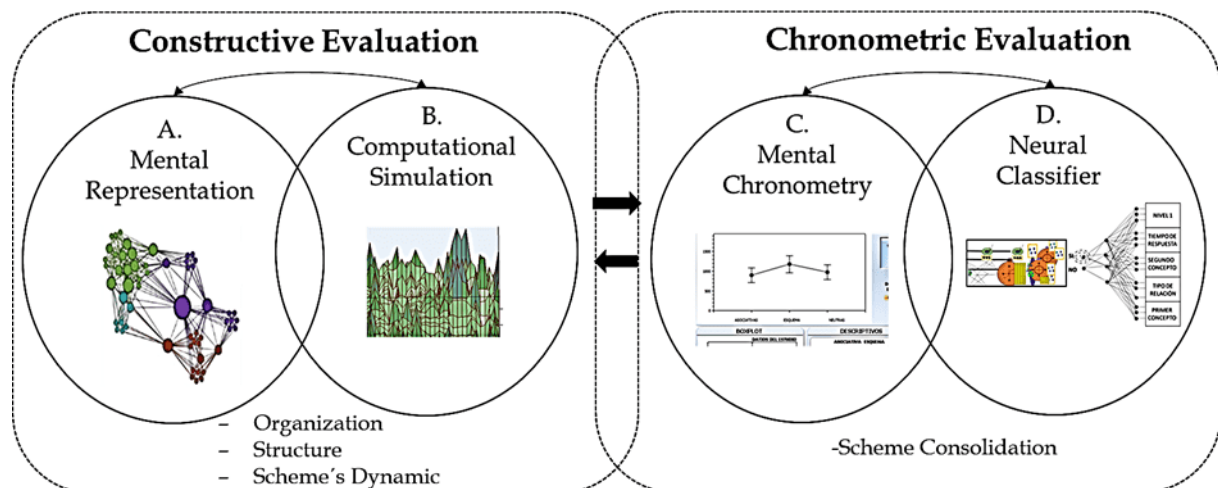


Figure 1. Phases and Components of C3-LEM (Morales-Martinez, Angeles-Castellanos et al., 2020)

Since the main focus of this paper is to illustrate the use of this model to measure the formation of knowledge structures related to computational cognition, the following section focuses on the development and application of the first evaluation phase of the C3 -LEM; namely the constructive cognitive evaluation of learning.

Constructive Cognitive Evaluation

Knowledge construction is a complex, multidimensional, and multifactorial process. Therefore, it is challenging for teachers to examine how students create knowledge structures through their academic learning experiences. Since no instrument can evaluate all aspects of a phenomenon as broad as learning, combining different approaches can help

overcome these difficulties. For example, in cognitive psychology, especially in cognitive science, memory assessment techniques can help to observe the origin and transformation of knowledge structures.

From the C3-LEM, the constructive cognitive evaluation of knowledge suggests applying mental representation techniques, such as the Natural Semantic Networks (NSN), to explore the formation of psychological knowledge meaning and reveal some of the cognitive characteristics of this process (Figueroa et al., 1976). For example, in the academic field, the NSNs help to observe the development of knowledge schemas acquired in different courses and allow the detection of cognitive changes in knowledge structures due to the learning process (Figure 2).

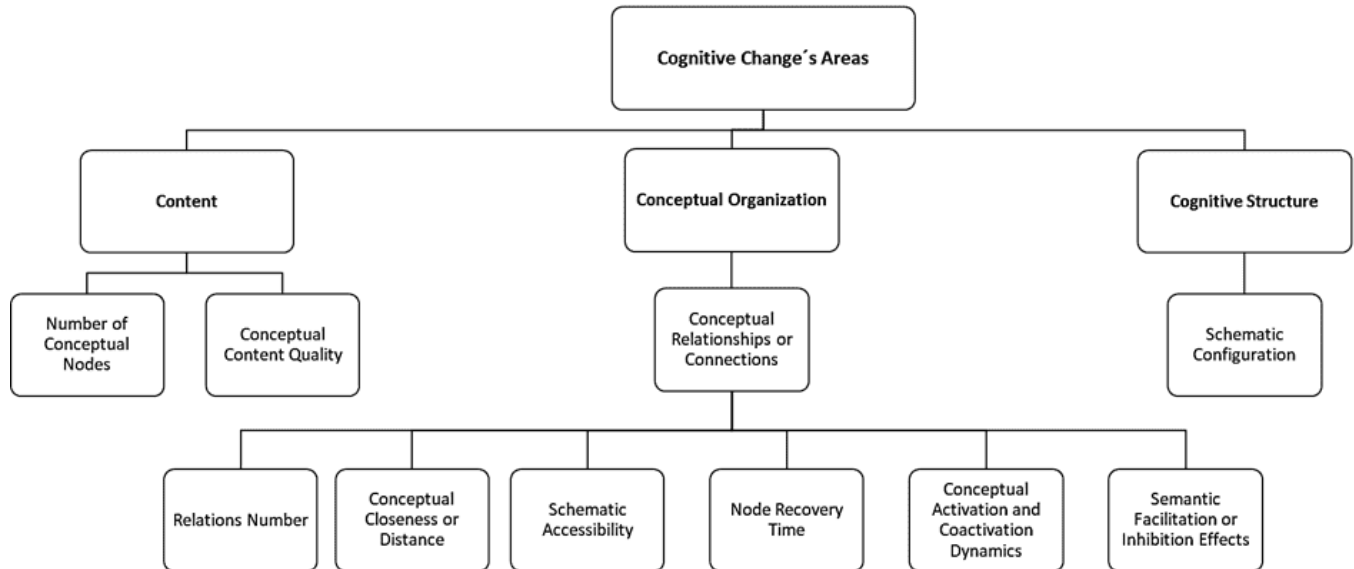


Figure 2. Examples of Areas of Cognitive Change in the Knowledge Structures that Can Be Observed Through the C3-LEM.

Morales-Martinez, Lopez-Perez et al. (2020) provide evidence about the utility of comparing the NSN at the entrance and at the end of a course to provide information on the effect of learning experiences on the formation of knowledge structures in the memory of students. They showed that NSNs are sensitive in measuring quantitative (e.g., number of concepts stored in a student's memory) and qualitative modifications (e.g., types of relationships between concepts saved in memory) in the information networks stowed in memory (Morales-Martinez, Angeles-Castellanos et al., 2020).

In general, constructive cognitive assessment studies using the NSN from the C3-LEM perspective suggest that the information quality in the students' knowledge networks reflects their level of academic development. In this matter, Morales-Martinez, Garcia-Torres et al. (2021), and Morales-Martinez, Mezquita-Hoyos et al. (2021) pointed out that students who are new to a topic present information selection and assimilation mechanisms with greater cognitive permeability to assimilate new information, compared to when they have greater expertise in a topic.

On the other hand, Morales-Martinez et al. (2017) reported that psychology students who enrolled for the first time in a cognitive development course entered with pre-schematic structures of the topic. They arrived with poorly organized cognitive structures, with basic or general concepts related to a lesser degree with the subject evaluated. Furthermore, they observed that the knowledge cognitive structure became more clearly configured and specified, and their concepts were organized more coherently as the course progressed. Also, the knowledge schema at the end of the course contained more technical concepts, and relationships among them were of better theoretical quality than the initial schema.

Consistent with the above, Morales-Martinez, Trejo-Quintana et al. (2021) observed that university students enrolled in a psychology course presented changes in the content specialization of their knowledge networks; the conceptual nodes tended to be more specific and closely related to the subject studied. On the other hand, Morales-Martinez et al. (2022) reported that the quality of mathematical concepts retrieved by engineering students differed according to their level of academic performance. Students with lower grades retrieved more general knowledge concepts on the subject. In contrast, students with outstanding grades retrieved more technical information on each subject evaluated. Medical students enrolled in an anatomy course (Morales-Martinez, Angeles-Castellanos et al., 2020) and engineering students enrolled in a computer interfaces course showed a similar cognitive performance pattern (Morales-Martinez et al., 2018).

The previous studies provide information on the possible types of change that may occur in the content, structure, and conceptual organization of students' knowledge schemas as a result of the learning experiences. However, comparison groups are needed to determine whether these changes occurred due to the general learning process that students obtained through their careers or whether they occurred as a result of receiving specific information on a topic. In this regard, the present study provides evidence that cognitive tools can provide indicators that discriminate between the changes that occur due to specific learning and those due to the global learning students obtain throughout their careers.

Methodology

The present authors conducted a cognitive diagnosis of learning at the beginning and end of the computational cognition course. The primary purpose was to observe the changes in the schematic behavior of students' knowledge structures due to the learning acquired in a course related to computational cognition. When students learn the content of a course, their memory presents changes in its content and structure, such as an increment in the schematic quality and accuracy of conceptual nodes, the addition or deletion of concepts, modifications in the conceptual relationships between the information nodes, variations in the semantic network's connectivity weight and changes in the accessibility level of the concepts. In this regard, the present study explores whether the changes observed in the NSN of the experimental and control groups are qualitatively and quantitatively different given the presence or absence of specific learning throughout the semester. Next, we describe the research design, the participating sample, the instruments, and the procedure for this study.

Research Design

The study design was a quasi-experiment with a pre-test-post-test control group. The authors measure students' knowledge state before and after a course about computational cognition by using NSN, a mental representation technique. This technique is a recall task with particular characteristics since they are obtained directly from participants (ecological validity). The recall tasks are typical procedures in mental representation studies. They provide very well-known memory indicators about the content, structure, and organization of knowledge schema stored in the memory.

In general, NSN requires the performance of a memory task restricted by time and by the relationship of the definers and the targets (for detail, see procedure). If students have stored specific knowledge from a course, they could retrieve technical information from their memories during the NSN task when the presentation of a target related to the course prepares the mind to access a knowledge schema learned during the course.

Although exploring a specific intervention type is not the core of the study, the teachers of both courses, along with the researchers, designed the course materials and activities in such a way as to guarantee that all students enrolled in these had the same opportunities to explore the content with care and very close teacher supervision (see instruments).

Sample and Data Collection

The study sample comprised 104 students enrolled in the first year of the Psychology Department (74 women and 30 men). Fifty percent of the students participated as an experimental group (enrolled in the Computational Cognition Course) and the rest as a control group (not enrolled in the evaluated course). The age range of the participants was 17 to 27 years old ($M = 19$, $SD = 1.7$). All participants were volunteers and gave their informed consent. The selection of participants was non-probabilistic. Each group came from a different institution to ensure that information about the specific content of the evaluated course would not be leaked in the control group.

Instruments

The design of the mental representation studies used the Protocol for the Collection of Target Concepts and Central and Deferred Definers by Morales-Martinez (2015), which is a teacher's guide to select the ten main concepts of the course to be evaluated (content validity). In this case, the ten main concepts were *mind*, *computation*, *computational mind*, *human information processing*, *von Neumann*, *Turing machine*, *connectionism*, *memory*, *working memory*, and *long-term memory*. These ten target concepts fed the Cognitive Evaluator software (EVCOG) to the design of the NSN study. This software follows the cognitive principles of the processing and learning of academic information proposed in the C3-LEM (Morales-Martinez, Garcia-Torres et al., 2021). In addition, EVCOG allowed the application and analysis of the data obtained in NSN studies.

Materials of the Course

Each teacher, along with the researchers, designed the materials for both courses. These included a set of ten readings, all designed under the same criteria. In order not to saturate the students' minds, each reading embraced the most relevant concept to the topic to study (no more than 20 main concepts). The readings included a brief questionnaire and a guide to performing a simple essay, considering all concepts that students could identify. Afterward, the students were given a cognitive consolidation activity to strengthen their learning about each subject.

Procedure

This investigation comprised two phases; during the first one, participants received information on the study purpose, the experimental task, their rights as participants, and the guarantee of their data's protection, and the participants gave informed consent. In the second phase, the experimental and control groups performed an NSN study before and after the course; however, while the first group received materials related to computational cognition, the control group took a general psychology course. Regardless of the course, teaching materials and activities were designed following the same criteria (see the instruments section) and applied with a similar school calendar.

The study task consisted in defining ten target concepts, which were randomly presented on a computer screen. Participants had sixty seconds to define each target using verbs, nouns, adjectives, and pronouns as definers. After defining each target, the participants rated the definers' quality, considering a scale of 1 to 10. Where 1 corresponded to the lowest degree of relationship between the definer and the target, the definer had a lower quality to define to the target. In contrast, closer to 10 denoted higher quality as a definer, as 10 was the highest semantic relationship between the definer and the target. The task consumed around 12 to 15 minutes, depending on the personal rhythm of each participant.

Analyzing of Data

The present authors examined the NSN study's data and obtained several indicators on the mental representation of knowledge proposed by Figueroa et al. (1976) and adapted by Lopez and Theios (1992). These included the J-value, which is semantic richness and accounts for the number of different definers used in a semantic network. The M-value is the semantic weight or relevance the participant gives to each definer. The G-value refers to the semantic distance between the concepts. The Q-value is an index of the similarity percentage between the initial and final NSN. The CCP-value is the conceptual change percentage or change percentage in semantic richness between both NSNs. The SAM group concerns the group of the ten definers with the highest M-value in each target.

Afterward, we visually inspected the organization and structure of the definers within the NSN using the data visual representation tool of the GEPHI software (Bastian et al., 2009). This software is free to use and allows a graphical representation of the connections between the information nodes extracted from information networks, such as the NSN of this study. The GEPHI software was fed with the SASO matrix (Semantic Analyzer of Schemata Behavior) (Lopez & Theios, 1992) or co-occurrence matrix between concepts, which results from the calculation with the following formula:

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

W_{ij} represents the association weight obtained by calculating the probability that two concepts (X and Y) do not co-occur $p(X = 1 \& Y = 0)$, $p(X = 0 \& Y = 1)$, or $p(X = 0 \& Y = 0)$ across the SAM groups. When both occur $p(X = 1 \& Y = 1)$, the calculation comprises a hierarchical modulation of the M-value in each SAM group and its interconnectivity through the neuro-computational network.

Findings / Results

We compared the NSN indicators and content of experimental and control groups' initial and final mental representations of computational cognition schema. The results indicated that the experimental group, on average, increased their semantic richness by 69.52%. The difference between the mean semantic richness (J-value) obtained at the beginning of the course ($M= 77.3$, $SD= 63.78$) and that shown at the end of the course ($M= 346.40$, $SD= 37.16$) was statistically significant ($t= -17.08$; $p < .001$). The concepts that showed a more significant increase in semantic richness were *von Neumann* (99.34%), *Human Information Processing* or *HIP* (98.02%), *Turing machine* (95.38%), and *connectionism* (95.25%). Those that showed less increase were: *mind* (62.10%), *long-term memory* (63.08%), and *memory* (61.09%) (Figure 3).

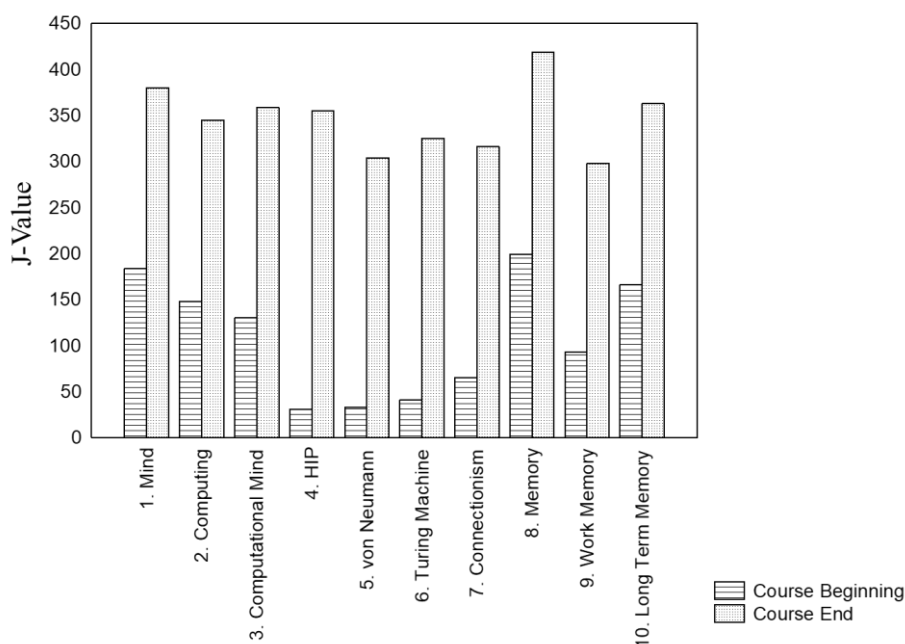


Figure 3. J-value for the Experimental Group, Before and After the Course Through the Targets.

In contrast, the control group showed an average decrease in the J-value of 7.4%. The difference between the mean semantic richness obtained by the participants of the control group at the beginning (M=182.40, SD= 69.67) and the end of the course (M=197.30, SD= 82.54) was not statistically significant ($t= 2.09$; $p = .06$). The concepts that showed a more significant decrease in semantic richness were: *computation* (-19.14%), *mind* (-18.98%), *von Neumann* (-17.46%), *working memory* (-15.16%), and those that showed an increase were: *PHI* (19.82%) and *computational mind* (3.12%) (Figure 4).

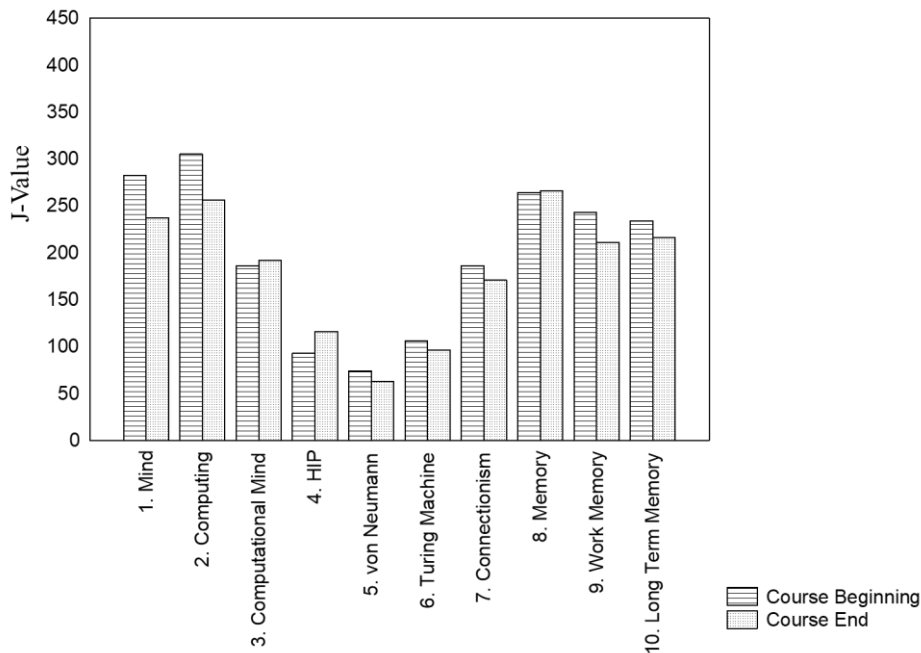


Figure 4. J-value for the Control Group, Before and After the Course, Through the Targets.

The target with the highest percentage of change in the semantic richness of the experimental group was *HIP* (91%), while that with the slightest change was *mind* (51%). Regarding the control group, the target with the highest percentage of change was *HIP* (20%). Moreover, the lowest percentage of change was *computational mind* (3%) (Figure 2 and 3, and Table 1). In addition to these changes, the experimental group presented variations in the SAM group's content at the end of the course. The experimental group's similarity index between the networks at the beginning and end of the course (Q-value) was shallow (8%), while in the control group, it was 38.25% (Table 1). The difference in the conceptual similarity index between the experimental and control groups was statistically significant ($t= -5.03$; $p < .001$).

Table 1. Conceptual Similarity Index for the Experimental and Control Groups Before and After the Course.

Target Concept	Group			
	Experimental		Control	
	CGP	Q-Value	CGP	Q-Value
Computation	57	0	-19	50.4
Working memory	69	0	-15	38.7
HIP	91	0	20	30.6
Long-term memory	54	4.5	-8	37.8
Von Neumann	89	5.4	-17	36.9
Computational mind	64	9.9	3	32.4
Memory	52	11.7	.75	49.5
Connectionism	79	15.3	-9	38.7
Turing machine	87	15.3	-10	24.3
Mind	51	18	-19	43.2
Mean	69	8.01	-7	38.25

Note. The table presents the conceptual growth percentage (CGP) for each target from the beginning to the end of the course and the similarity index (Q-value) between the experimental and control group's initial and final NSN.

Table 2 presents an example of the content change in the *HIP*'s SAM group for both groups, experimental and control, from the beginning to the end of the course. The first group showed a shallow similarity index between both networks (*HIP*, Q-value = 0), and the control presented a high Q-value (*HIP*, Q-value = 30.6). In addition, the reader can note that the experimental and control groups in their initial network used definers from general knowledge. Also, participants

tried associating the target with psychology schema using their common sense (e.g., *psychology, perception*). A third solution for participants was to use definers from another knowledge schema (e.g., *mathematics, value, volume*). However, during the second measurement, there was a shift in the experimental group towards using concepts more related to the learned knowledge schema (e.g., *information, structure, processes, duration*). In contrast, the control group continued to use common sense definers (e.g., *letters, Greek*) or definers belonging to the general schema of psychology (e.g., *Gestalt, phenomenon*), or another knowledge schema (e.g., *mathematics, numbers*).

Table 2. Change in the Content of HIP's SAM for the Experimental and Control Group.

Experimental Group		Control Group	
HIP (CGP = 91; Q-Value = 0)		HIP (CGP = 20; Q-Value = 30.6)	
Initial NSN	Final NSN	Initial NSN	Final NSN
Mathematics	Information	Numbers	Phenomenon
Psychology	Process	Mathematics	Movement
Symbol	Postulates	Letters	Letters
Value	Human	Movement	Gestalt
Volume	Symbols	Lights	Mathematics
Technique	Structure	Infinite	Numbers
Values	Mind	Alphabet	Acronyms
Brain	Processes	Decimal	Lights
Perception	Psychology Cognitive	Greek	Psychology
Chemistry	Duration	Circle	Greek

Note. The table presents the content changes in HIP's SAM for the experimental and control groups from the beginning to the end of the course. Also, it showed the conceptual growth percentage (CGP) and the similarity index (Q-value) between the initial and final NSN for each group.

In addition to changes in the content and specificity of schema content after the course, the student's knowledge schema also showed changes in the definers' appearance frequency throughout the NSN. In the experimental group, the most frequent concepts at the beginning of the course were: *brain* (F=8), and *mind* (F=5), while those with a minor appearance (F=1) included *cognition, symbol, person, and short-term memory*. While in the final NSN, the most frequent definers were: *information* (F=8) and *processes* (F=7), and among those with a minor appearance (F=1) were: *memory, Turing, serial, distributed memory, and artificial neurons*. On the other hand, the definer with the highest frequency of appearance in the initial NSN of the control group was *processes* (F=7). Among those with the lowest appearance (F=1) were: *Turing, connections, and history*. The most frequent definers in the final NSN were: *brain* (F=5) and *processes* (F=5), and some of the least frequent (F=1) were: *immediate, remembering, and learning*.

Also, the students' computational cognition schema changed the definers' connectivity degree towards the end of the course. The GEPHI plot (Figures 5 and 6) illustrates the connectivity degree of the definers in the NSN through the conceptual node's size. Conceptual nodes with more connections in the NSN are larger than those with fewer connections to other definers. In the initial NSN of the experimental group (Figure 5), the concepts with the highest connectivity were: *brain, psychology, technology, computer, memories, neurons, and work*. However, in the final NSN, they were: *information, processes, structures, store, compute, processing, and processor*. These conceptual relevance changes provide information about the psychological meaning change of the experimental group's knowledge schema, which went from a general view of the mind to a cognitive view of information processing.

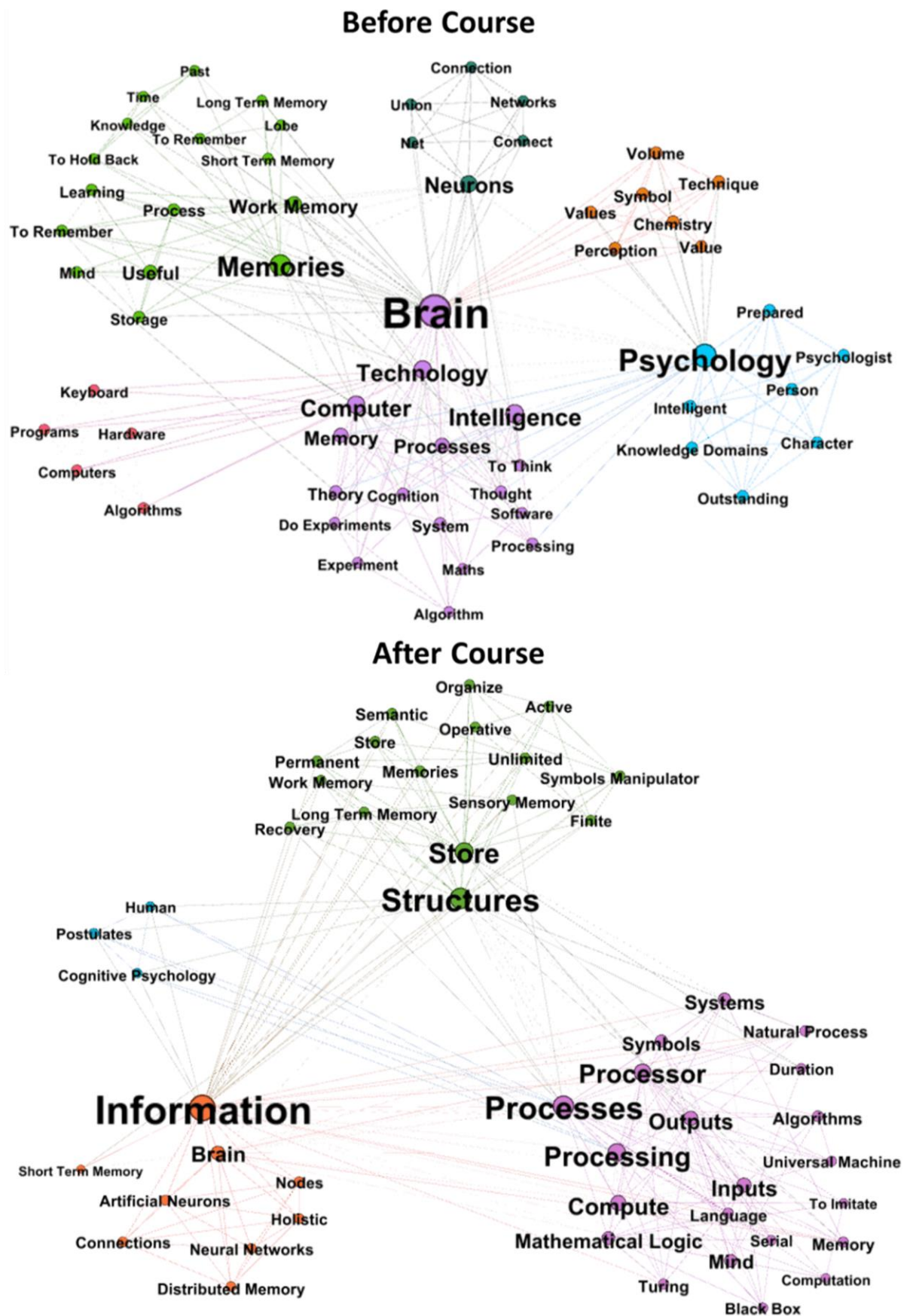


Figure 5. Graphic Representation of the Computational Cognition Schema of the Experimental Group at the Beginning and the End of the Course.

Furthermore, the Gephi charts above show the organizational, structural, and content changes of the NSNs after the course. In this regard, the experimental group organized their conceptual nodes (definers) into six groups at the beginning of the course (Figure 5). The first one (purple) involved 28.81% of the definers of the NSN (*brain, technology,*

computer, intelligence, memory, cognition, theory, thinking, thought, software, processes, algorithm, system, experience, processing, experiment, mathematics).

The second group (lime green) included 27.12% of the definers (*memories, working memory, process, useful, storage, mind, remember, learning, STM, memory, lobe, LTM, retain, time, knowledge, past*). The third group (light blue) agglomerated 13.56% of the definers (*psychology, intelligent, knowledge, outstanding, prepared, psychologist, character, person*). The fourth group (orange) included 11.86% of the definers (*values, symbol, chemistry, volume, perception, technique*). The fifth cluster (dark green) grouped 10.17% of the definers (*neurons, connection, networks, contact, union*), and the last group (pink) included 8.47% of the definers (*hardware, programs, computers, keyboard, algorithms*).

The experimental group organized the definers into four groups at the end of the course (Figure 5). The first (purple) grouped 42.86% of the definers (*processes, processing, processor, computing, systems, duration, natural process, algorithms, universal machine, symbols, inputs, imitate, serial, outputs, mind, language, Turing, memory, computation, mathematical logic, black box*). The second (green) included 32.65% of the definers (*structures, store, SM, WM, retrieval, unlimited, permanent, store, LTM, memories, operational, finite, symbol handler, active, organize, semantic*). The third cluster (orange) comprised 18.37% of the definers (*information, brain, LTM, nodes, artificial neurons, holistic, connections, neural networks, distributed memory*), and the fourth cluster (light blue) included 6.12% of the definers (*humans, postulates, cognitive psychology*).

On the other hand, Figure 6 shows that the changes in the definitional content of the control group's final NSN correspond to the integration of information from general psychology schemas very different from the evaluated course, in contrast to the experimental group. For example, at the beginning of the course, the control group considered processes, memory, brain, computer, and machine to be the definers with greater connectivity in the NSN. In contrast, towards the end of the course, the definers with the highest connection were: *memory, processes, brain, computer, thought, technology, human being, ideas, and mind*. Although the final NSN of the control group aligns to a great extent with the conceptual nodes at the initial NSN, their organization is different.

At the beginning of the course, the participants organized the definers of their NSN into five groups (Figure 6). The first (purple) included 34.33% of the NSN definers (*brain, memory, ability, unlimited, memory type, consciousness, useful, thought, temporary, think, intangible, STM, LTM, mind, remember, thought, memories, work, software, systems*). The second group (lime green) integrated 25.37% of the definers (*machine, computer, processor, invention, intelligence, mouse, technology, world war, first, keyboard, internet, Alan Turing, device, computation, innovation, CPU, programs*). The third grouping (light blue) involved 14.93% of the definers (*letters, movement, circle, numbers, alphabet, infinity, decimal, mathematics, Greek*). The fourth conglomerate (orange) comprised 13.43% of the definers (*ideas, connections, union, philosophy, relates, current, theory, connect, concepts*). The fifth grouping (dark green) included 11.94% of the definers (*science, name, theoretician, person, character, scientist*).

In the second measurement, the control group participants reorganized their concepts into five groups (Figure 6). Although the content and organization varied, it was not significantly different. The first grouping (purple) included 32.26% of the defining concepts (*brain, processes, memory, information, STM, storage, work, memories, retrieval, recall, software, systems, immediate, thought, cognition, abstract, learning, LTM, consciousness, thoughts*). The second group (lime green) collected 25.81% of the definers (*thought, computer, technology, science, machines, psychology, invention, computation, innovation, device, mouse, matter, internet, screen, keyboard*). The third cluster (light blue) gathered 14.52% of the definers (*mind, ideas, association, relationships, current, connections, union, theory, philosophy*). The fourth group (orange) grouped 14.52% of the definers (*lights, movement, phenomenon, Gestalt, mathematics, letters, numbers, acronyms, Greek*). Finally, the fifth group (dark green) clustered 12.9% of the definers of the NSN (*human being, subject, man, name, character, story, mammal, person*).

Discussion

One of the most relevant challenges of the 21st century education is the creation of learning evaluation tools that embrace new technological resources without neglecting the complexity of learning, which include both the visible expressions and the cognitive process of learning itself (Morales-Martinez, García-Torres et al., 2021). In this regard, the present work presented a cognitive proposal for the combined use of new technologies and cognitive evaluation tools to create evaluation instruments that allow for measuring both the process and the product of academic learning through cognitive indicators from the mental representation of knowledge under the C3-LEM.

The use of constructive cognitive evaluation tools allowed the present authors to approach the question of the cognitive changes that students present in the knowledge schema of computational cognition. Furthermore, the cognitive measurement tools allowed us to observe whether these cognitive changes in mental structures differ from those presented by students of similar ability but who have not studied this particular knowledge schema. The results indicated that the students' knowledge structures underwent modifications in their content, organization, and configuration due to learning over the period of the course. These changes are different from those seen in students who study psychology but did not directly receive the technical content of the evaluated course.

The study data suggest that learning in this course affected the quality and quantity of the content of students' knowledge structures. Indeed, the experimental group showed a significant increase in their semantic richness level related to the course (Figure 3), especially in those concepts directly related to computational models of the mind (*von Neumann, HIP, Turing machine, and connectionism*). In contrast, the concepts pertaining to other topics in psychology (*memory, LTM, mind*) changed to a lesser degree.

The increase in J-value after studying a topic has also been observed in other studies on different domains of knowledge (Morales-Martinez, 2020). However, there has been little discussion about the increase in semantic richness in specific target concepts. The present authors hypothesized that the cognitive conceptual permeability level in targets might be related to the issue of expertise. In this study, the participants showed a remarkable increase in the J-value in the targets of relatively new topics. In contrast, incorporating more information was not as pronounced in targets with greater theoretical familiarity to the students. In this regard, Morales-Martinez, Garcia-Torres et al. (2021), Morales-Martinez, Trejo-Quintana et al. (2021), and Morales-Martinez, Mezquita-Hoyos et al. (2018) suggested that the level of academic development influences the mechanisms of selection and assimilation of student information. When students are novices in a subject, their cognitive permeability to assimilate new information is greater.

In summary, this study's results suggest that the experimental group's academic mastery of specific topics (target concepts) influenced their cognitive permeability to incorporate or not incorporate more new concepts. In contrast, the control group did not show a significant increase between their initial and final semantic richness, even when they took courses that were in some way related to cognition subjects (Figure 4). On the contrary, this group showed a decrease in the percentage of conceptual change in most of the targets (Tables 1 and 2).

A possible explanation for this is that the cognitive change pattern in the initial and final J-value observed in the experimental group is directly related to the specific intervention of a course and not necessarily related to the exposure of other courses related in a general way to the evaluated subject. On the other hand, the control group's cognitive changes are the product of general learning in a psychology career.

On the other hand, in this study, the experimental group showed a broad change in their NSN content, as the Q-value adjustment disclosed (Table 1 and 2). In this regard, Morales-Martinez, Trejo-Quintana et al. (2021) mentioned that students seemed to enter the courses with pre-schemas, or at least that they attempt to build these cognitive structures prior to the course in order to have a base on which to organize new knowledge. The flexibility of these pre-schemas to change depends mainly on their structuring and sophistication level. The more consolidated the schema, the less flexibility it will have to reorganize, reconfigure and change its content (Morales-Martinez, Garcia-Torres et al., 2021; Morales-Martinez, Mezquita-Hoyos et al., 2021). Thus, the drastic change in the NSN semantic richness of the experimental group may indicate that their pre-schemas were poorly consolidated because they had received little information on the subject. Their cognitive learning curves would have been different if they had been in a more advanced course, with a more extensive background on the subject.

Increasing semantic richness does not necessarily imply a favorable change in the content of knowledge schemas after academic learning. Examining the content of NSN gives information about the cognitive nature of changes in the organization and structure of knowledge schemas due to academic learning. Regarding this, Morales-Martinez, Trejo-Quintana et al. (2021) provided evidence related to the change in the specificity level present in the conceptual nodes' content after the students had passed a course. Along this same line, the results of the present study showed that the experimental group used more technical concepts at the end of the course to define each central concept. For example, they used common sense definers (e.g., person, outstanding) to define von Neumann's goal at the beginning of the course, while at the end of the course, this group used more sophisticated definers (e.g., universal machine, serial) to define this target (Figure 5).

In addition, the GEPHI plot of the experimental group showed a change in the centrality of certain definers. For example, the *brain* represented a central node at the beginning of the course. However, by the end of the course, this conceptual node had less connectivity. Another instance is *information*, which did not appear in the initial phase of the course but appeared towards the end as one of the most relevant conceptual nodes. This result denotes a change in the meaning of the targets and definers. Therefore, it indicates a change in the understanding of the subject due to learning. Also, the results in Figure 5 illustrate that the knowledge schema of the experimental group underwent a modification in the number of groupings. At the beginning of the course, the students organized their schema into a six-dimensional model; afterward, they reorganized and reconfigured their NSN into four dimensions. The control group did not show this ability to synthesize the concepts into fewer clusters after the course. However, its organization was different, and at the end of the course they reduced the schema fracture from two separate groups to one (Figure 6).

It is possible that the conceptual sifting of the definers unrelated to the evaluated schema and the acquisition of information that was more coherent and related to the learned topic allowed the students to organize and structure their knowledge schema more clearly. These changes were also observed in other knowledge domains, such as biology (Urdiales-Ibarra et al., 2018) and computational interfaces (Morales-Martinez et al., 2018), whereby students showed changes in their schematic structure and organization. However, their cognitive patterns differ according to their level of academic development or performance (see Morales-Martinez, Angeles-Castellanos et al., 2020).

Conclusion

The results of this study indicated that the cognitive evaluation tools and their indicators included in the present study are sensitive in detecting the changes that occur in the student's cognitive structures as a consequence of learning. Moreover, these tools make it possible to compare and distinguish between the patterns obtained from students who have had specific training and those who have not. These tools could help create diagnostic and formative evaluation models of the level of academic development in a specific knowledge domain and allow cognitive characterization in forming academic knowledge structures. This type of information can empower teachers and students, giving them awareness of the dynamics of the learning process and thus promoting students' metacognitive skills.

Recommendations

This study showed the usefulness of the NSN technique for contrasting the content and organizational properties of a knowledge schema on cognitive psychology under two conditions. The first one comprised exposure to a specific topic on computational cognition, and the second involved exposure to the general knowledge schema of psychology. Therefore, it is necessary to carry out further investigations in other knowledge domains, using larger samples and including participants from different educational and academic development levels, in order to observe the behavior of the reported phenomenon under new contexts. Increasing the number of participants would allow for exploring whether learners' groups with different cognitive styles may organize the information and structure differently depending on their particular characteristics. On the other hand, exploring different knowledge domains would allow researchers to observe whether students in different fields of study approach cognitive learning in different ways, depending on the nature of their study object.

Limitations

Due to the nature of the sample, the data cannot be generalized to other contexts in the same knowledge domain. In addition, since the C3-LEM has been tested in a few areas of knowledge and with a small number of samples, it is not possible to know whether the results obtained in this sample are common patterns regardless of the teaching style, curriculum, level of expertise, and area of knowledge.

Authorship Contribution Statement

Morales-Martinez: Conceptualization, design, statistical analysis, data acquisition, interpretation, drafting the manuscript. Garcia-Collantes: Conceptualization, data cleaning, interpretation. Lopez-Perez: Data cleaning, critical revision of manuscript, editing/reviewing.

References

- Arieli-Attali, M. (2013, October 20–25). *Formative assessment with cognition in mind: The cognitively based assessment of, for and as learning (CBALTM) research initiative at educational testing service* [Paper presentation]. 39th Annual Conference on Educational Assessment 2.0: Technology in Educational Assessment, Tel Aviv, Israel. <https://doi.org/10.13140/2.1.3555.7129>
- Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: An open-source software for exploring and manipulating networks *Proceedings of the International AAAI Conference on Web and Social Media*, 3(1), 361-362. <https://doi.org/10.1609/icwsm.v3i1.13937>
- Conway, M. A., Cohen, G., & Stanhope, N. (1992). Very long-term memory for knowledge acquired at school and university. *Applied Cognitive Psychology*, 6(6), 467-482. <https://doi.org/10.1002/acp.2350060603>
- El-Yassin, H. D. (2015). Integrated assessment in medical education. *Journal of Contemporary Medical Sciences*, 1(4), 36–38. <http://bit.ly/3ZG7Sct>
- Figuroa, J. G., González, E. G., & Solís, V. M. (1976). An approach to the problem of meaning: Semantic networks. *Journal of Psycholinguistic Research*, 5(2), 107-115. <https://doi.org/10.1007/BF01067252>
- Lopez, E. O., & Theios, J. (1992). Semantic analyzer of schemata organization (SASO). *Behavior Research Methods, Instruments, & Computers*, 24(2), 277-285. <https://doi.org/10.3758/BF03203508>
- Lopez-Ramirez, E. O., Morales-Martinez, G. E., Hedlefs, M. I., & Gonzalez, C. J. (2014). New empirical directions to evaluate online learning. *International Journal of Advances in Psychology*, 3(2), 40-47. <http://bit.ly/3FjiSEI>
- Marzano, R. J. (1994). Lessons from the field about outcome-based performance assessments. *Educational Leadership*, 51(6), 44-50. <https://bit.ly/3YgXRBf>
- Morales-Martinez, G. E. (2015). *Protocolo para la recolección de conceptos objetivo y definidores centrales y diferidos: Un sistema de codificación de conceptos extraídos de las redes semánticas naturales* [Protocol for the collection of target concepts and central and deferred definers: A coding system for concepts extracted from natural semantic networks] [Unpublished manuscript]. Institute of Research on the University and Education, National Autonomous University of Mexico.
- Morales-Martinez, G. E. (2020). *Sistema de evaluación cognitiva constructiva cronométrica del aprendizaje en línea y presencial* [Online and face-to-face learning's constructive-chronometric cognitive assessment system] [Manuscript submitted for publication]. Institute of Research on the University and Education, National Autonomous University of Mexico.
- Morales-Martinez, G. E., Angeles-Castellanos, A. M., Ibarra Ramirez, V. H., & Mancera Rangel, M. I. (2020). Cognitive e-tools for diagnosing the state of medical knowledge in students enrolled for a second time in an anatomy course. *International Journal of Learning, Teaching and Educational Research*, 19(9), 341-362. <https://doi.org/10.26803/ijlter.19.9.18>
- Morales-Martinez, G. E., Garcia-Torres, M., Castro-Gonzalez, M. C., & Mezquita-Hoyos, Y. N. (2021). The measurement of knowledge construction in a course of diagnostic evaluation of learning disorders in psychology students. *International Journal of Learning, Teaching and Educational Research*, 20(8), 240-261. <https://doi.org/10.26803/ijlter.20.8.15>
- Morales-Martinez, G. E., Hedlefs-Aguilar, M. I., Trejo-Quintana, J., Mezquita-Hoyos, Y. N., & Sanchez-Monroy, M. (2021). Chronometric constructive cognitive learning evaluation model: Measuring the consolidation of the human cognition schema in psychology students' memory. *International Journal of Learning, Teaching and Educational Research*, 20(5), 56-72. <https://doi.org/10.26803/ijlter.20.5.4>
- Morales-Martinez, G. E., Lopez-Perez, R. M., Garcia-Collantes, A., & Lopez-Ramirez, E. O. (2020). Evaluación constructiva cronométrica para evaluar el aprendizaje en línea y presencial [Constructive-chronometric evaluation as a tool to evaluate online and face-to-face learning]. *Tecnología, Ciencia y Educación*, 15(1), 105–124. <https://doi.org/10.51302/tce.2020.371>
- Morales-Martinez, G. E., & Lopez-Ramirez, E. O. (2016). Cognitive responsive e-assessment of constructive e-learning. *Journal of e-Learning and Knowledge Society*, 12(4), 39-49. <https://doi.org/10.20368/1971-8829/1187>
- Morales-Martinez, G. E., Lopez-Ramirez, E. O., Castro-Campos, C., Villarreal-Treviño, M. G., & Gonzales-Trujillo, C. J. (2017). Cognitive analysis of meaning and acquired mental representations as an alternative measurement method technique to innovate e-assessment. *European Journal of Educational Research*, 6(4), 455-464. <https://doi.org/10.12973/eu-jer.6.4.455>

- Morales-Martinez, G. E., Lopez-Ramirez, E. O., & Lopez-Gonzalez, A. E. (2015). New approaches to e-cognitive assessment of e-learning. *International Journal for e-Learning Security*, 5(2), 449-453. <https://doi.org/10.20533/ijels.2046.4568.2015.0057>
- Morales-Martinez, G. E., Mezquita-Hoyos, Y. N., Gonzalez-Trujillo, C. J., Lopez-Ramirez, E. O., & Garcia-Duran, J. P. (2018). Formative e-assessment of schema acquisition in the human lexicon as a tool in adaptive online instruction. In R. Lopez-Ruiz (Ed.), *From natural to artificial intelligence: Algorithms and application* (pp. 69–88). IntechOpen. <http://doi.org/10.5772/intechopen.81623>
- Morales-Martinez, G. E., Mezquita-Hoyos, Y. N., Hedlefs-Aguilar, M. I., & Sánchez-Monroy, M. (2021). Cognitive assessment of knowledge consolidation in a course on the diagnostic evaluation of learning disorders in psychology students. *International Journal of Learning, Teaching and Educational Research*, 20(10), 95-116. <https://doi.org/10.26803/ijlter.20.10.6>
- Morales-Martinez, G. E., Trejo-Quintana, J., Charles-Cavazos, D. J., Mezquita-Hoyos, Y. N., & Sánchez-Monroy, M. (2021). Chronometric constructive cognitive learning evaluation model: Measuring the construction of the human cognition schema of psychology students. *International Journal of Learning, Teaching and Educational Research*, 20(2), 1-21. <https://doi.org/10.26803/ijlter.20.2.1>
- Morales-Martinez, G. E., Villarreal-Lozano, R. J., Izaguirre-Lerma, J., & Santos-Alcantara, M. G. (2022). Diagnóstico cognitivo del conocimiento matemático en estudiantes de Ingeniería [Cognitive diagnosis of mathematical knowledge in engineer students]. *Innovación Educativa*, 22(88), 57-77. <http://bitly.ws/ATy3>
- Moreno, R. (2010). *Educational psychology*. John Wiley & Sons, Inc.
- Urdiales-Ibarra, M. E., Lopez-Ramirez, E. O., Castro-Campos, C., Villarreal-Treviño, M. G., & Carrillo-Colon, J. E. (2018). Biology schemata knowledge organization and meaning formation due to learning: A constructive-chronometric approach to concept mapping usability. *Creative Education*, 9(16), 2693-2706. <https://doi.org/10.4236/ce.2018.916203>