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Cognitive Technology to Evaluate the Academic Learning of Computational Cognition in Psychology Students

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Abstract: This study illustrated an alternative way to evaluate students' academic learning. It involved the joint and intertwined application of the natural semantic network technique, computer simulations, and semantic priming experiments to assess the cognitive changes in knowledge structures due to academic learning in two groups of psychology students. The experimental group was enrolled in a course on computational cognition, while the control group was oblivious to this course. The results indicated that the cognitive assessment tools discriminate the cognitive changes produced as a result of general training undertaken in a psychology degree versus the influence of a specific course. After the course, the experimental group increased their technical vocabulary, changed their conceptual valuation of definers related to computational theories of mind, and reorganized the relations among definers according to the computational cognition approach. Also, this group presented a higher connectivity index between the concepts of the semantic network, their conceptual activation level and conceptual co-activation pattern changed, and their access level to the evaluated schema's concepts improved. In contrast, the control group did not show significant changes in their cognitive patterns after the course. These findings suggest that cognitive tools may be helpful in the diagnosis of academic learning.

Keywords: *Academic learning, cognitive assessment, natural semantic networks, psychology students, semantic priming.*

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Introduction

Learning assessment is one of the most exciting challenges of the 21st century education, requiring evolution in the vein of teaching models and technology advancements and in regard to understanding society's emerging needs. In addition, determining aspects of learning assessments and how they should be evaluated in educational settings is a major, very difficult task (National Research Council [NRC], 2001; Nichols & Sugrue, 1999). Most academic tests measure students' short-term memory skills as knowledge acquisition; for example, teachers administer multiple-choice, true-false, or open-question tests at the end of a course to verify whether the student has retained learned knowledge. The correct answer is proof of the student's acquired knowledge, but such conventional evaluation does not determine if a student has developed a long-term cognitive ability; many students use strategies to pass exams without engaging in meaningful long-term learning (Marzano, 1994; Marzano & Costa, 1988; Marzano et al., 1990).

A contemporary evaluation of academic learning requires the use of evaluation tools to measure abilities related to cognitive information processing, which are central to training 21st-century students, who live in an economy largely dependent on information management (Arieli-Attali, 2013). However, there are scarce alternatives embracing this modern vision of learning, technology developments, and advancements in science learning. In line with this concern, the NRC (2001) used the advancement of cognitive science to rethink assessment approaches, since advances in cognitive science expanded the knowledge surrounding important learning dimensions. Further, its advances in measurement techniques open possibilities to understand and interpret increasingly complex evidence relating to the academic performance of students.

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In consonance with the NRC's vision, Morales-Martinez et al. (2023) highlighted the usefulness of cognitive assessment tools to evaluate the process and results of learning, since measurement advances in cognitive psychology are compatible with new technologies. The intertwined use of cognitive paradigms to study the human mind with computational developments offers an opportunity to create or innovate digital methods to approximate the learning assessment, as is illustrated in the next section.

Literature Review

The proposal of linking cognition and learning theories with learning assessment practices and teaching is not a new concept (see NRC, 2001), Arieli-Attali (2013) noted how since the previous century, there have been sophisticated approaches to enchain cognitive science with learning assessment. More recently, Lopez-Ramirez et al. (2014) proposed the Chronometric Constructive Cognitive Learning Evaluation Model, or C3 LEM, which works under the principles of serial and parallel human information processing and provides cognitive tools that explore how the student's mind works when forming knowledge structures.

Conventionally, the C3 LEM suggests using intertwined chronometric and mental representation techniques to assess academic learning processes (selection, storage, and retrieval of the information stored in the students' memory). The application of C3-LEM involved two phases (Figure 1): the constructive cognitive evaluation and the chronometric cognitive evaluation of knowledge. The first assesses the meaning formation on knowledge mental representation and reveals their cognitive characteristics (the conceptual organization, structure, and dynamic) through mental representation techniques (Natural Semantic Networks) and computational simulations.

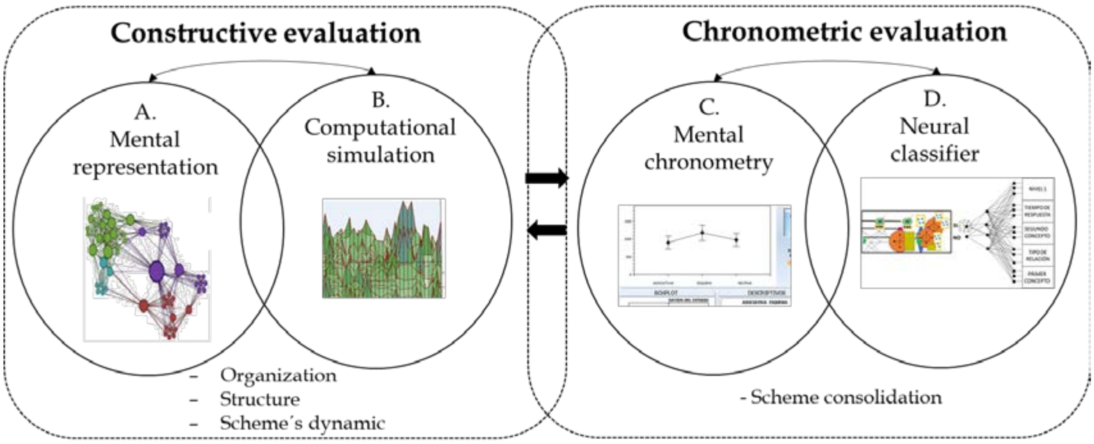

Figure 1. Phases and Components of the C3-LEM (Morales-Martinez, Angeles-Castellanos, et al., 2020)

The Natural Semantic Networks (NSN) technique (Figueroa et al., 1976) is a methodological approach to studying mental representation, which implies the recovery of information from human memory by using conceptual clues (targets). This technique is useful for exploring the development of knowledge schemas acquired throughout the academic year. According to Morales Martínez, López Pérez, et al. (2020), applying an initial NSN in a course and comparing it to the final NSN allows for observation of the qualitative (content) and quantitative cognitive changes due to academic learning. Comparison of both NSN, initial and final, involves contrasting several indicators such as the semantic richness (number of conceptual nodes), semantic relevance of the concepts (M value), and the Inter-Response Times (temporary patterns of definers appearance), among others.

The NSN technique requires a definition task; participants define core target concepts of the academic course using definers (nouns, verbs, adjectives, pronouns). Following this, they rate these definers based on their relationship degree with the target (Morales-Martinez, Angeles-Castellanos, et al., 2020). These scores support the computational simulations of the knowledge schema's behavior at the beginning and end of the academic year (Lopez-Ramirez et al., 2014). Lopez-Ramirez et al. (2015) used this technique to explore schematic activity in academic learning across different knowledge domains. Furthermore, computer simulations can indicate connections among concepts only observed with these tool types. For example, Gonzalez et al. (2013) observed that high school students established implicit relationships among concepts of an NSN on moral course. They observed the concept of *parent* co-activated *police*, even though these concepts appear semantically unrelated. However, when the researchers considered the social and cultural context of the participants, they noted a relationship of psychological significance.

In general, the NSN analysis and the computer simulations allow us to observe the changes in the mental representation of students' knowledge produced by learning a knowledge domain. Combining these techniques with experimental cognitive studies increases the potential to evaluate other relevant aspects of academic knowledge as the temporal patterns of schematic behavior. For example, the implementation of chronometric cognitive evaluation studies helps obtain temporal trends in the capacity to access information from memory.

Morales-Martínez and Santos-Alcantara (2015), following the proposal of E.-O. López-Ramírez (personal communication, August 9th, 2014), used the Inter-Response Time (IRT) of NSN to analyze the information accessibility level. These authors reported that the definers with the greatest weight tend to appear between 30 and 40 seconds, and they appeared between the third and fifth positions on the list. However, there was no discussion about what this positioning means. It is unknown if this is the case for all knowledge domains and which variables influence the recovery of academic concepts.

In addition to IRT, reaction times (RT) are another indicator of the chronometric cognitive evaluation; these come from schematic word recognition studies applied before and after the course. The RT can be classified through a neural network to discriminate whether there was an integration of the academic content into students' long-term memory structures at the end of a course. To achieve this, the C3-LEM includes the application of the semantic priming paradigm throughout lexical decision tasks (McNamara, 2005), which consists of presenting word pairs with different relationship types (e.g., associative, categorical, schematic, unrelated). The experimental task is to mentally read the first (prime) and the last (target) word and decide whether the target is spelled correctly.

The recognition times of targets offer information about how the context preceding schematic words affects students' information processing. Suppose the presentation of a stimulus (word or image) is preceded by another semantically related stimulus. In that case, students will recognize the second stimulus more quickly or accurately than in the case of no semantic relationship between the two stimuli. In a C3-LEM study, the semantic relationships between the schematic word pairs are relevant. If the knowledge schema does not exist in the student's memory at the beginning of the course, and by the school year end, students have integrated the information into their knowledge structures, the recognition time of schematic pairs will significantly reduce by the course end.

Lopez (1996) and Lopez and Theios (1992) proposed that the semantic priming effect produced by a schematic relationship is a concept termed "schematic priming." In academic learning, schematic priming is present just for those word recognition tasks that involve concepts related to the knowledge schema of the evaluated course. The evidence from cognitive studies shows that when a student stores the conceptual nodes learned in class in his long-term memory, the word recognition times related to the learned schema decrease at the course end (e.g., see Gonzalez et al., 2013; Morales Martínez, López Pérez, et al., 2020). The opposite happens when students do not consolidate the information in their memory (Urdiales-Ibarra et al., 2018). In short, this type of knowledge organization cognitive phenomenon in long-term memory (schematic priming) can account for a learning process on academic knowledge schemas.

Techniques such as those involved in the C3-LEM can be valuable tools in the assessment for, as, and of learning (see Morales-Martinez, 2020; Morales-Martinez & Lopez-Ramirez, 2016; Morales-Martinez et al., 2015, 2017), thus, it is essential to accumulate evidence of the worth of this cognitive approach to evaluate learning effectively. Therefore, using this evaluation model, this research explored the changes in students' knowledge structures due to the learning conducted in a face-to-face psychology course. The first question in this research was to determine the pattern of cognitive knowledge structure changes that students experience after learning a specific topic (Computational Cognition). The second question was to discriminate the pattern of cognitive changes among students enrolled and not enrolled in the course; as the results of this study pointed out, there are differences in cognitive patterns related to expertise in this field. The cognitive measurement tools accounted for cognitive differences between the change directed by specific learning and the spontaneously produced by non-systematic exposure to general psychology education.

Methodology

Research Design

The present authors used a qualitative and quantitative mixed method (C3-LEM) to measure the cognitive dimension of academic learning in a Computational Cognition course. First, they designed and applied an NSN study; then, they performed a computational simulation on the data of this first study using a neural network of constraint satisfaction proposed by Lopez and Theios (1992). Finally, they implemented experimental research through the semantic priming paradigm.

Sample

Two groups of first-year psychology students participated in this study (74 women and 30 men). The first attended a computational cognition course (experimental group), and the second was the control group, which did not have access to the information on the subject evaluated. The control and the experimental groups came from different institutions. The participants had a mean age of 19 years (range 17 to 27 years, SD= 1.7). Participation was voluntary, and all participants gave informed consent.

Instruments

The authors selected ten stimuli from the theory discussed in the course (mind, computation, computational mind, HIP, von Neumann, Turing machine, connectionism, memory, working memory, and long-term memory) to design the NSN study. Concept selection followed Morales-Martinez's Protocol for the Collection of Concepts (Morales-Martinez, 2015), which consists of several conceptual analysis steps on the subject for evaluation. This is a guide to selecting target concepts to create the NSN study as well as 30 definers to design the semantic priming experiment. The authors organized the definers in prime-target pairs (e.g., software-processes, algorithm-language, and memory-processor). Furthermore, they added 15 associative concept pairs (e.g., bee-sting, airplane-pilot, dentist-tooth) and 15 unrelated word pairs (e.g., floor-screen, mountain-blood, war-elevator).

Procedure

This research involved an announcement, where the students received an invitation to participate voluntarily, also they learned about the study objectives and benefits, and the authors gave a privacy warning about their data. Following this, the students who chose to participate gave their informed consent and received specific instructions for NSN and semantic priming study tasks. Finally, the students completed both tasks, and the authors performed a computer simulation on the data from the first study.

Natural Semantic Network Study: The Mental Representation of Knowledge

The participants performed a conceptual definition task, which involved defining ten target concepts that embraced the computational cognition topic. The targets appeared randomly, one by one, and remained in the computer screen's center for 60 seconds. The participant defined each target with verbs, nouns, adjectives, and pronouns and later qualified individually the conceptual quality of each definer concerning its target. As Lopez (1996) and Lopez and Theios (1992) suggested, conceptual scores varied between one and ten; the smaller the number, the lower the quality of the schematic relationship between the definer and its target.

Computer Simulation: The Schematic Dynamics of Knowledge Structures

Data obtained from the NSN study fed a constraint-satisfaction neural network using EVCOG software. The computational simulation procedure followed Lopez and Theios' (1992) formula:

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

X and Y represent pairs of concepts. Obtaining the association grade among X and Y requires calculating the p(X = 1 & Y = 0) value by determining the joint probability that X appears when Y does not appear in a SAM group. Furthermore, p(X = 0 & Y = 1) and p(X = 0 & Y = 0) are calculated similarly. Calculating the p(X = 1 & Y = 1) value considers a hierarchical modulation of the M value in each SAM group and their interconnectivity through the neuro-computational network. These calculations served to configure a connectivity matrix (SASO Matrix) (Semantic Analyzer of Schemata Behavior) (Lopez & Theios, 1992) useful for the semantic analysis of schematic behavior.

Semantic Priming Study: The Mental Chronometry of Academic Learning

Finally, a semantic priming study determined the degree of learned information consolidation in the student's memory. The study presented pairs of words (prime-target) that could have different relationship kinds (associative vs. schematic vs. unrelated). Figure 2 illustrates the experimental sequence.

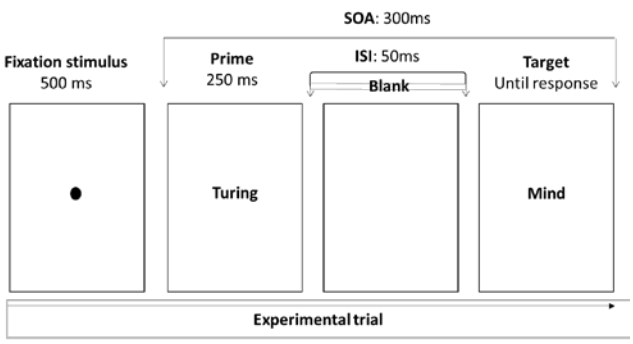

Figure 2. The Sequence of an Experimental Test of the Semantic Priming Study

The experimental sequence consisted of a black dot in the computer screen center presented for 500 ms, after the first concept appeared (prime) for 250 ms. Finally, the last word (target) appeared and remained on the screen until the participant performed the experimental task, which consisted of reading each pair of words (prime-target) silently and then making a lexical judgment about the target. The participant categorized the last word as 'word' or 'no word'. The study duration ranged from 7 to 9 minutes, depending on the participant's performance.

Data Analysis

First, the authors performed a multidimensional scaling analysis on the first study's data to inspect the organization of the participants' schema. After, they carried out a computational simulation through a constraint-satisfying neural network. This kind of tool facilitates the observation of knowledge schema activation and co-activation behavior. Finally, a third analysis explored the chronometric patterns of information processing related to the evaluated course. The authors obtained the IRT (the time each student used to recover each definer of the NSN from their memory). Following this, they applied a mixed ANOVA on the RT obtained in both the experimental and control groups' semantic priming study to determine the consolidation level of information in the student's memory at the beginning and the end of the course.

The authors carried out analysis of variance with consideration that the level of measurement of the dependent variable was ratio. The observations had a condition of independence as the experimental conditions and the participants were assigned randomly for this study. Regarding equinormality in the data, the QQ plot showed that the data distribution was normal, while Levene's test showed that the variances were equal across the experimental conditions for both the control group and the experimental group.

Results

The authors organized the results in three dimensions: the first describes the content and organization of the knowledge schema on computational cognition. The second is the observation of the schematic dynamics and connectivity pattern of the NSN. The last dimension examines the conceptual accessibility and consolidation of the information in the learned schema.

Schema's Content and Organization Analysis

A multidimensional scaling analysis revealed that the experimental group presented changes in the conceptual organization and quality of the definers related to computational cognition. While they used concepts from a mixed psychology and technology general schema in the course beginning, toward the course's end, the students organized their concepts in two conceptual axes under a specialized schema related to computational cognition (Figure 3). One axis involved HIP (Human Information Processing) and PDP (Parallel Distributed Processing) concepts. The second axis incorporated concepts related to the body-mind duality issue from a cognitive perspective, otherwise known as the hardware-software metaphor.

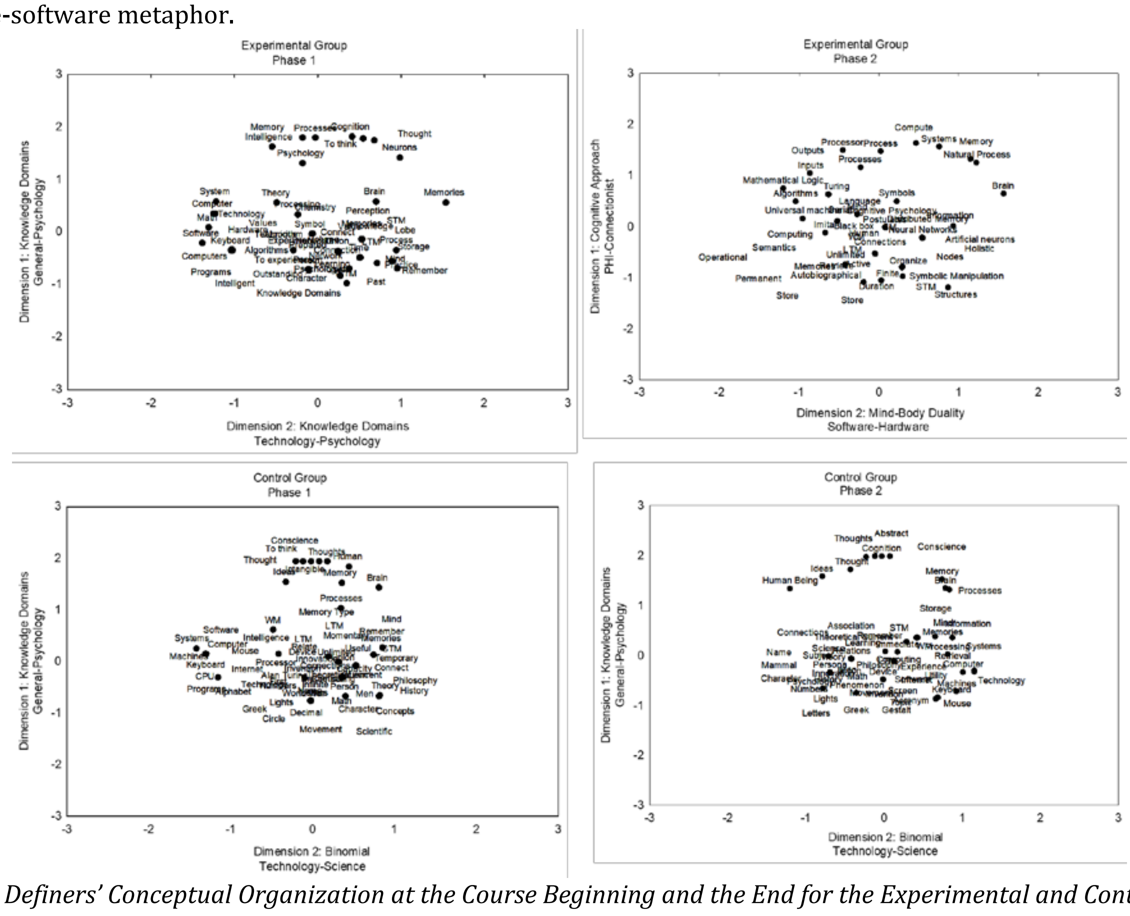

Figure 3. Definers' Conceptual Organization at the Course Beginning and the End for the Experimental and Control Group

In contrast, although the control group incorporated new concepts towards the course end, they belonged to a general psychology schema, and their organization remained relatively similar at the course beginning and end.

Connectivity Patterns and Schema Dynamics

Academic learning expression also includes the formation of new connections, the loss of existing ones, or the change in connection weights. Figure 4 shows the changes in the initial and final connections between the targets evaluated by the experimental and control groups. Notice in the figure that the experimental group increased the number of connections on different targets. For example, at the beginning of the course, they connected computation only with three targets (computational mind, Turing machine, and HIP); after the course, participants formed six new connections (von Neumann, long-term memory, working memory, connectionism, memory, mind) with this same concept for nine final connections. Furthermore, they lost conceptual nodes, disconnected *long-term memory*, and *von Neumann*, and formed a connection between the Turing machine and *computation*. Also, participants increased or decreased the connectivity strength among different targets. For example, the computational mind-von Neumann pair strengthened their relationship by increasing the number of common definers from one to five toward the course end.

The control group gained and lost connections and changed connection strength among different target pairs. However, the control group had very little change in concepts such as HIP compared to the experimental group's performance.

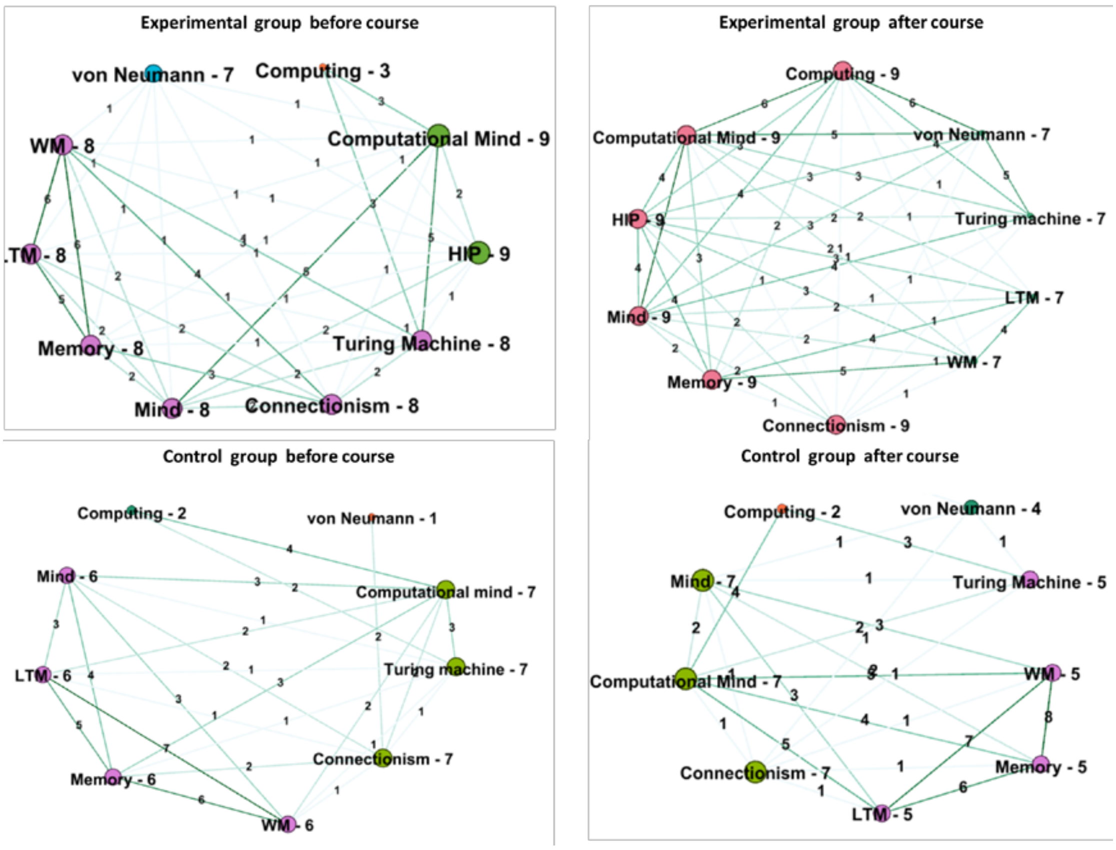

Figure 4. Connectivity Graph Obtained Before and After the Course by the Experimental and Control Group

Note. A color node represents each target, and the node's size is related to the connectivity degree. The definers' number connecting each target pair is over the linking line. The more definers connect each target pair, the darker the line.

On the other hand, the authors analyzed two aspects to explore the schematic behavior: the levels of schema activation before and after the course and the co-activation pattern among definers. In both cases, the SASO matrix helped graph the schema behavior. The results indicated that only the experimental group's schema activity was significantly modified. By contrast, in the control group, the activation remained similar between the initial and final measurements (Figure 5). The experimental group increased its conceptual activation level at the course end, as shown in Figure 5, where greater activation is presented with a red and higher graph position.

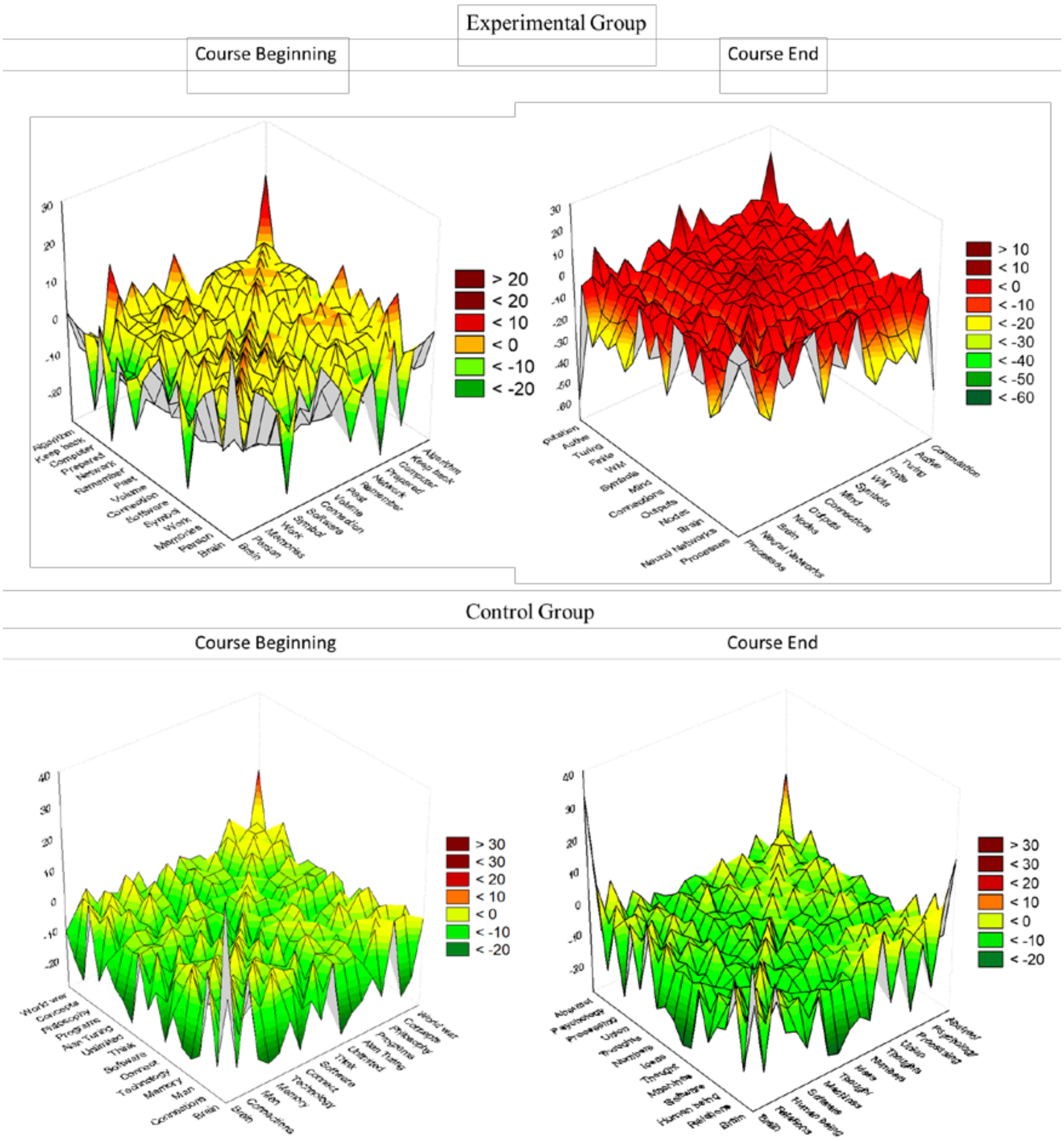

Figure 5. Experimental and Control Group Surface Plots

The authors illustrated the co-activation schema patterns by activating common concepts with the highest M values in the experimental group (Figure 6) and these concepts experienced a meaning change at the course end. In this regard, *the brain* went from a vision directly associated with memory to a cognitive science view (neural networks). *The computer* passed from a classical computation schema toward a human information processing vision. However, these concepts did not experience any change in the control group.

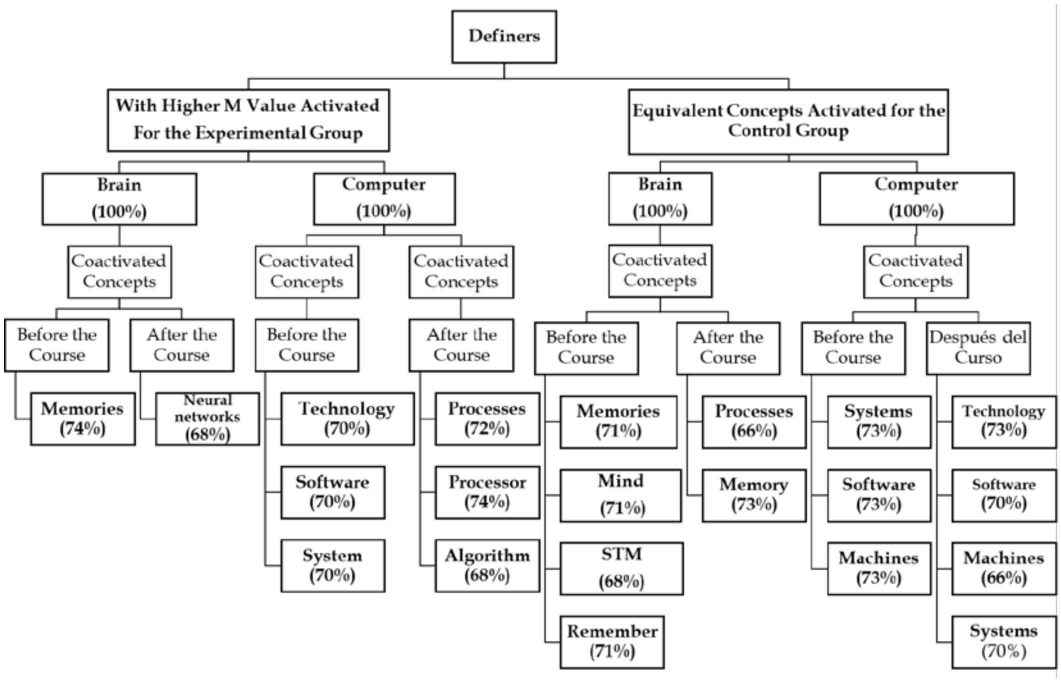

Figure 6. Patterns of Co-Activation for Two Definers with the Two Highest M Values in Both Groups

Mental Chronometry and Consolidation of the Schema

A qualitative analysis of the experimental group's IRT revealed that the relation among conceptual accessibility of definers in their M values is negative (Figure 7). The correlation increased significantly for the experimental group at the end of the course (r = -.31) compared with the initial NSN (r= -.16). This means that after students learned computational cognition schema, they accessed definers with the highest M value in a shorter time than when the concepts obtained less semantic relevance. Similarly, the control group exhibited a correlation change from the initial NSN (r = -.42) to the final NSN (r = -.55).

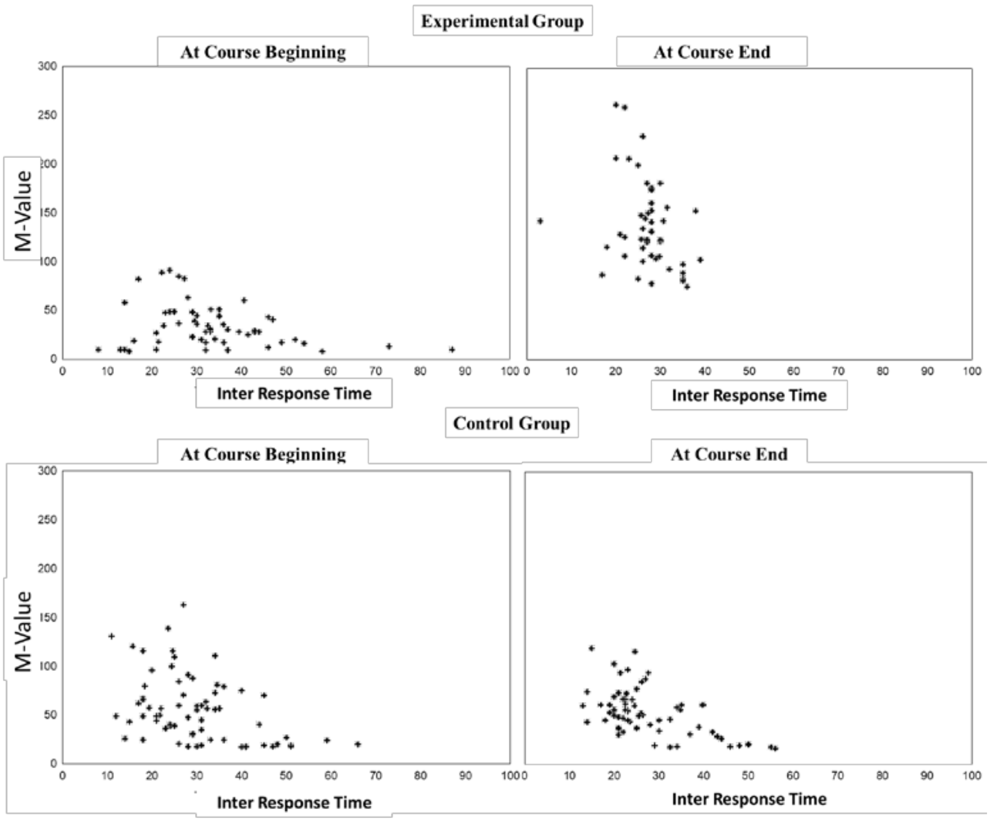

Figure 7. Relationship Between the Inter-Response Times and the M Values Obtained for All the Definers by the Experimental and Control Groups at the Course Beginning and End

The experimental group changed in the pattern of access time and semantic relevance of definers (Figure 7). However, a student's t test for dependent samples, performed on the access times on the common definers obtained before (M = 30, SD = 9.6) and after the course (M = 27, SD = 3.1), indicated that there was not a statistically significant difference. The scarcity of common definers and the high variability in the IRT from the course beginning likely influenced this result. On the other hand, a student's t-test was also applied to the M values obtained in the common definers before (M = 62, SD = 23) and after (M = 148, SD = 50) the course, and the difference was statistically significant ($t(8) = -4.17$, p = .004).

On the other hand, the control group showed greater changes in the M values than in the common definers' IRT distribution. In this regard, a student's t-test ($t(42) = .85$) indicated that there are no significant differences between the IRT means obtained for the commons definers at the course beginning (M = 29, SD = 10) and the end (M = 28, SD = 9.2). However, there was a significant difference ($t(42) = -2.77$, p = .008) between the M value means of the initial (M = 65 SD = 37) and final NSN (M = 56 SD = 24). Figure 8 shows these changes in the interaction pattern between IRT and M-value, only for the common definers between the initial and final NSN.

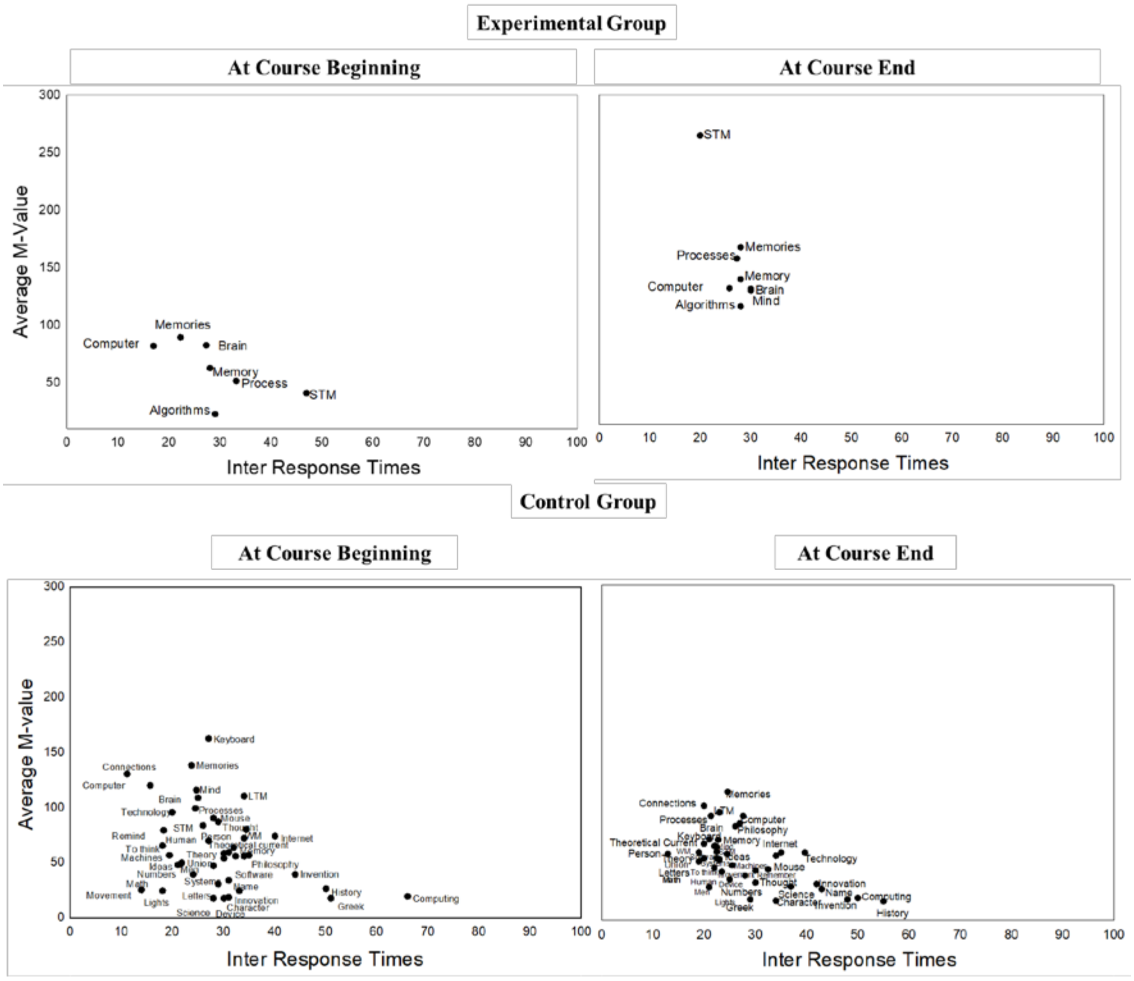

Figure 8. Relationship Between the Inter-Response Times and the M Values Obtained for the Common Definers by the Experimental and Control Groups at the Beginning and End of the Course

The final chronometric analysis comprised a mixed ANOVA of 2(Group: Experimental vs. Control) x2(Course time: Start vs. End) x3(Semantic relationship: Associative vs. Schematic vs. None) on reaction times obtained in the semantic priming experiment (Table 1). The significance level was at $p \leq .05$. The analysis included only the reaction times for the correct answers for 45 participants in each group. The authors eliminated those participants who did not obtain at least 70% correct answers in the experimental conditions in any of the two measurement moments.

Table 1. Mixed ANOVA for the Study of Semantic Priming Experiment

Factor	Effect		Error		F	*p*	η_p^2
	df	*SM*	*df*	*SM*			
Group (G)	1	856974.340	88	185470.554	4.621*	.03	.04
Measurement time (T)	1	1925325.066	88	31119.173	61.869*	.00	.41
Semantic relation (R)	2	1717560.012	176	10595.469	162.103*	.00	.64
G*T	1	643701.362	88	31119.173	20.685*	.00	.19
R*G	2	10656.501	176	10595.469	1.005	.36	.01
T*R	2	161678.605	176	9007.069	17.950*	.00	.16
T*R*G	2	30817.479	176	9007.069	3.421*	.03	.03

Note. N= 90; *ANOVA* = analysis of variance; *df* = degree freedom; *SM* = square mean; $\eta_p{}^2$ = partial eta squared. *$p \leq .05$

According to Table 1 and Figure 9, there was a significant difference in the performance by group factor. Figure 9 shows a different reaction time pattern for both groups. There was a significant difference between initial and final reaction times through all the conditions. However, according to the results of the post hoc comparisons (Tukey HSD test), these differences were only significant for the experimental group in all conditions: associative (p =.006), schematic (p =.001), and no relationship (p =.004), while for the control there were no significant differences in any experimental condition: associative (p =1.00), schematic (p = .39) and no relationship (p =.82).

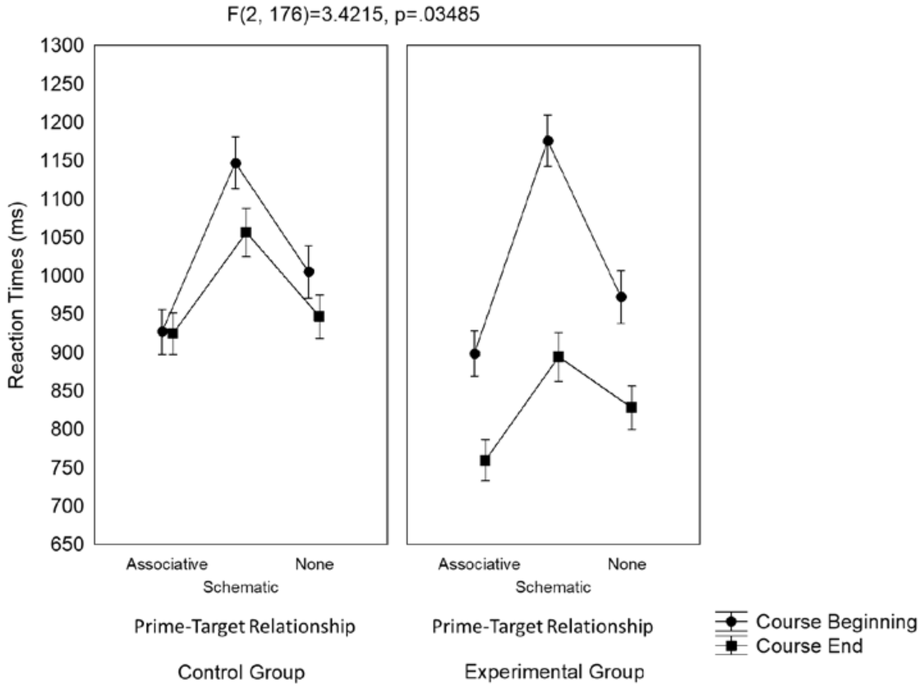

Figure 9. Interaction Graph Among the Factors of the Semantic Priming Study

Discussion

The present study illustrated the usefulness of cognitive assessment tools to innovate, create or modify academic learning evaluation. The cognitive assessment tools used in this study allowed us to assess the cognitive dimension of knowledge acquisition about computational cognition. In this regard, the present authors discuss the results related to the changes in the conceptual organization, dynamics, and accessibility of the evaluated schema.

The data indicated that, towards the end of the semester, only the experimental group incorporated technical concepts related to computational cognition and presented a conceptual reorganization that reflected two schematic axes of computational cognition. The first was related to the revised theoretical approaches (HIP and PDP), and the second was linked to the mind-body debate, which is closely linked to the hardware-software dyad (Figure 3). Changes in conceptual organization due to academic learning are rarely discussed (see Morales-Martinez, Trejo-Quintana, et al., 2021). These types of conceptual changes reflect the schematic relations governing the order of output of the definers towards the end of the course, which could indicate whether a teacher's course contributed to a mental representation of the content in the students' minds. In addition, it also suggests that the knowledge structures achieved a certain level of stability consistent with the theoretical approach that the student reviewed in the course.

Regarding the changes in the NSN connectivity of the experimental group, there was an increment in the connections' number and strength among the network nodes; also, some connections disappeared (Figure 4). In this regard, Morales-Martinez, Garcia-Torres, et al. (2021) mention that students with schemas prior to a course are less flexible when it comes to changing the connection pattern. In the present study, the experimental group's flexibility in changing the connection pattern among NSN targets might be associated with the fact that the experimental group was a beginner in the computational mind topic. In addition, changes in the way targets connect suggest that the students re-signified the target according to the knowledge acquired. A previously irrelevant concept can gain more weight through the network by increasing its inputs or outputs either from or to other conceptual nodes.

On the other hand, the experimental group had a lower activation level at the course beginning than towards the end. The control group did not obtain differences in this aspect (Figure 5). Lopez-Ramirez et al. (2015) showed how this type of change occurred when a student learned the academic content. However, the author did not present comparisons with the control group. Therefore, the present study shows empirical evidence that these changes in the activation patterns of the schema do not occur randomly. The computer simulation results suggest that the experimental group changed the meaning of common concepts. For example, the activation of the computer at the beginning co-activated concepts related to a technology schema, while, at the end, this concept co-activated words more related to a vision of computational cognitive processing (Figure 6). In contrast, there was no evidence of meaningful change in the activated concepts for the control group.

Regarding the chronometric analysis of the schematic behavior, the analysis of the IRT in the NSN study showed that the experimental group decreased their access time to the schema definers (Figure 7.). In particular, the change in the temporal access pattern to common definers (Figure 8.) suggests that learning about these concepts allows the student to recover the information stored in their memory more quickly. As pointed out by Morales-Martinez, Hedlefs-Aguilar, et al. (2021), there is little information on how to interpret these changes in the access time to information. However, considering the results of this study in other learning dimensions (organization and structure), the time access to concepts can improve because the students have more efficiently organized the information in their memory. Furthermore, it is possible that the connections between the nodes strengthened; therefore, the co-activation was more effective among conceptual nodes. This result indicates the need to explore which factor makes it easier for students to be more efficient in retrieving certain information. The inverse relationship between the M and IRT values suggests that the changes in definer meanings may influence information access time.

Finally, the semantic priming study experimental group significantly decreased RT in schema concept recognition (Table 1 and Figure 9). The difference in size between the RT at the course beginning and end was more significant in the schematic words than in the other two experimental conditions. However, it was impossible to determine if this improvement in schematic word recognition time was due to greater consolidation of the learned information in the student's memory since the participants also showed an improvement in recognizing unrelated and associative words. The presence of an effect of practice and the variability present in the responses did not allow the experimental effect to be observed clearly. In future applications, it would be convenient to increase the number of experimental trials to counteract this possible extraneous variable. In contrast, the control group had a practice effect, but they did not significantly improve their word recognition times under any of the conditions.

Therefore, the previous results confirm that the assessment tools from the field of cognitive sciences are helpful in the academic learning evaluation field. Also, they are useful for discriminating when a student has received training in a specific field. Furthermore, the data from this study support the idea that the C3-LEM can be used across different fields of knowledge, which is in line with the results of other studies that evaluate academic learning through this model (see Morales-Martinez, Angeles-Castellanos, et al., 2020; Urdiales-Ibarra et al., 2018). Furthermore, the findings on this study suggest that the C3-LEM is useful regardless of the teaching style; however, there is no discussion about the potential use of this type of evaluation to detect the effect that each teacher exerts on student learning. In this regard, Rodriguez's (2021) results suggest that students from different groups form dissimilar representations of the knowledge learned in classes even when they reviewed the same topic under similar conditions but with different teachers.

Conclusions

The present study shows how the use of evaluation tools from mind cognitive science can be adapted to explore students' cognitive reality during the formation of academic knowledge structures. It contributes to the solution search to face the challenge of creating evaluation tools more in line with the new needs of a context that requires technology and knowledge management skills. Also, this study's results provide evidence of how knowledge structures evolve systematically depending on the student's exposure to certain materials and the effort made to learn the information. Finally, this work is an invitation to innovate, create or use the new digital media and methodological resources of learning science to face the challenges in the field of academic learning assessment.

Recommendations

The present study showed the usefulness of cognitive assessment instruments to discriminate the patterns of cognitive change that occur in knowledge structures due to learning a specific subject compared to those cognitive changes that occur because of general training received in the psychology career. However, the study field with the C3-LEM remains open; for example, it is not clear if this learning evaluation model can detect the specific effect of different teaching styles or learning styles on students´ constructive process of knowledge structures. If so, future research could focus to determine how students´ cognitive mechanisms of organization, structure, access, and knowledge use changed depending on exposure to a particular teaching strategy or the researchers could compare if students form different representation kinds depending on their preferences or tendencies to study.

Limitations

The study yielded interesting data on the cognitive nature of changes in knowledge structures due to academic learning; however, the evidence provided is limited to a single domain of knowledge in a specific field. In addition, the study did not consider variables associated with learning, such as cognitive and learning styles. There was also no analysis of mental representation given the sex of the participant because the sample was small, and the number of women was more significant than the number of male participants.

Ethics Statements

The studies involving human participants were reviewed and approved by the National Autonomous University of Mexico. The participants provided their written informed consent to participate in this study.

Authorship Contribution Statement

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

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