Research on associative cognition networks with educational robotics for learning healthy hydration habits

Investigación en redes asociativas de cognición para el aprendizaje con robótica educativa de hábitos de hidratación saludable

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Abstract

Introduction: Neuroeducation establishes the need to analyze cognitive structures in order to assess learning. The demand of technological advancement necessitates the increase of digital resources for teaching and scientific and digital literacy.
Objective: Analyses *Associative Cognitive Networks* of pre-service teachers on bioscientific learning of healthy hydration habits after an intervention using educational robotics.
Methodology: The study adopts a mixed approach and graph analysis using Gephi® and Cytoscape® software, and with the use of measures of *Degree*, *Clustering coefficient*, *Average Shortest Path Length* and *Modularity*.
Results: *Milk* is represented as the main *Hub* of the cognitive structures. The nodes with the highest *Degree* are located in the center of the network, such as *Milk*, *Natural juice*, *2 liters of water, 200 ml of wate*r or *Sweetened beverages*, while *Energy drinks* and *Natural lemonade*, which have the lowest relevance, are located further away.
Discussion: There is a reasonable association between healthy and unhealthy drinks, as well as a strong association between water consumption and healthy drinks, especially milk. The pre-service teachers have a better understanding of the concept of recommended daily intake compared to the number of specific glasses.
Conclusions: Scientific knowledge acquired after educational robotics intervention focuses on relevant content for healthy hydration habits. To improve assessment in higher education, it is advocated more studies analyzing *Associative Cognitive Networks* on the effects of learning scientific content and the use of resources such as Educational Robotics.

Keywords

Cognition; health education; higher education; robotics.

Resumen

Introducción: La neuroeducación establece la necesidad de analizar las estructuras cognitivas para evaluar el aprendizaje. La demanda del avance tecnológico hace necesario el incremento de recursos digitales para la enseñanza y la alfabetización científica y digital.
Objetivo: Analizar las *Redes Asociativas de Cognición* de maestros en formación sobre el aprendizaje biocientífico de hábitos saludables de hidratación tras una intervención con Robótica Educativa.
Metodología: El estudio adopta un enfoque mixto y análisis de grafos utilizando los softwares Gephi® y Cytoscape®, y mediante medidas de *Grado*, *Coeficiente de agrupamiento*, *Longitud media del camino más corto* y *Modularidad*.
Resultados: La *Leche* se representa como *Hub* principal de las estructuras cognitivas. Los nodos con mayor grado se sitúan en el centro del grafo, como *Leche*, *Zumo natural*, *2 litros de agua, 200 ml de agua* o *bebidas azucaradas*, mientras que las *Bebidas energéticas* y *Limonada natural*, que tienen la menor relevancia, se sitúan más lejos.
Discusión: Existe asociación razonable entre las bebidas saludables y no saludables, así como una fuerte asociación entre el consumo de agua y las bebidas saludables, especialmente la *Leche*. Los maestros en formación comprenden mejor el concepto de ingesta diaria recomendada en comparación con el número de vasos específicos.
Conclusiones: Los conocimientos científicos adquiridos tras la intervención de Robótica Educativa se centran en contenidos relevantes para los hábitos saludables de hidratación. Para mejorar la evaluación en la educación superior, se aboga por más estudios que analicen las *Redes Asociativas de Cognición* sobre efectos del aprendizaje de contenidos científicos y el uso de recursos como la Robótica Educativa.

Palabras clave

Cognición; educación para la salud; educación superior; robótica.

Introduction

The study of the brain and its functioning continues to be one of the fundamental research strategies in our present world. Understanding the mechanisms underlying cognitive processes such as memory, attention and learning provides a scientific basis for developing more effective and personalized educational methods (Luchini et al., 2024). Cognitive neuroscience reveals how different teaching strategies can influence neural plasticity and optimize learning. This knowledge makes it possible to design interventions that are adapted to the needs of students, improve academic performance, and more effectively address learning difficulties (Siew, 2020).

The neuroanatomy of memory is divided into two sets of structures: cortical and subcortical. The cortical structures include the frontal, temporal, parietal and occipital lobes. Although their neurophysiological underpinning is very complex, it can be noted that the frontal lobe is crucial for working and prospective memory (Frankland and Bontempi, 2005), while the temporal lobe is mainly associated with autobiographical memory and spatial perception, as well as long-term memory (Ward, 2010). The parietal lobes are mainly involved in spatial skills and orientation, as well as verbal short-term memory. And finally, the occipital lobe, located above the cerebellum, is mainly responsible for visual perception and the transmission of this information to other cortical areas (Kandel, Schwartz and Jessell, 1991; Westmoreland, 1994).

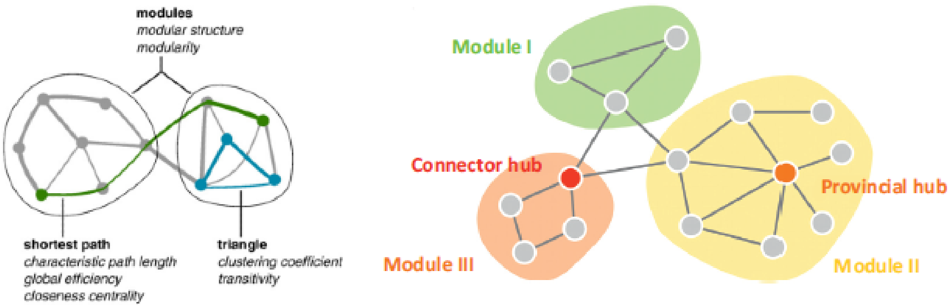
Thus, the main subcortical structures are the hippocampus, amygdala and cerebellum. The hippocampus is essential for the consolidation of short- and long-term memory and the representation of cognitive maps. The amygdala, located below the hippocampus, is involved in emotional memory and motivation. And the cerebellum encodes motor and procedural memories, contributing to skill and movement memory (Mahut, Zola-Morgan and Moss, 1982; Mishkin and Appenzeller, 1987; Ward, 2010).

The composition and number of neurons and synapses in the nervous system form neural networks, where mathematics has explored them since the 17th century and increased since 1980 for artificial intelligence and Bayesian cognitive science (Baronchelli et al., 2013; Puga et al., 2007). Connectome maps have identified key anatomical Hubs in the brain, such as the precuneus and cingulate cortex, and functional hubs such as the thalamus, essential for memory and perception (Hwang et al., 2021).

The theory of mathematical graphs has allowed highlighting crucial elements of the nervous system, also being applied to the cognitive sciences to improve the understanding of student learning through methods of representation of latent knowledge (Siew, 2019). As a result of this, Associative Cognition Networks (ACN) appear, being visualizations of mental models composed of nodes and edges, which are modified with brain development and lobe structure. Intelligence is related to the complexity of these layouts, and during learning, people construct or reconstruct their ACN (Román, 2021; Stella, 2022). That is, through the qualitative analysis of these nodes and edges obtained on the learning or knowledge of a content, and supported by graph theory, the functional representation of these mental models can be obtained, through Communities. There is a growing body of evidence supporting the use of network analysis for the assessment of student learning (Jones et al., 2014).

A key issue in the analysis and representation of networks is quantitative measurements. In this sense, 3 scales are established: micro-level (structural properties of individual nodes), meso-level (subsets and substructures), and macro-level (global structure of the network) (Siew, 2020). Regarding the micro-level, the Degree measure stands out, which refers to the number of immediate connections that a node has. A high Degree node has many closely related neighbors, while a low Degree node has few. This Degree has implications for the efficiency of concept retrieval and integration of a new concept into memory (Siew, 2020). As a consequence, the Hub concept (high Degree node) is generated, whose deletion causes a greater impact on the cognitive network (Siew, 2019). Another relevant metric is the Local Clustering Coefficient, which is calculated as the proportion of connections between its neighboring nodes; this is acquired by the number of closed triangles relative to the total number of possible triangles (Figure 1).

Figure 1. Measures of graph analysis (Rubinov and Sporns, 2010; Van den Heuvel & Sporns 2013).

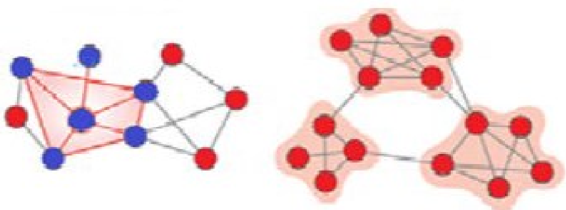


Regarding the macro-level, the measures provide an indication of the overall structure. Some of these measures are micro-level averages, such as the *Average Degree* or *Global Clustering Coefficient*. Another important measure is the *Average Shortest Path Length* (ASPL), which quantifies the *Average Shortest Path Length* among all possible pairs of nodes.

Related to the meso-level we find the concept of *Modularity* (Q). While the *Local Clustering Coefficient* (CC) measures the connectivity between neighboring nodes, *Modularity* measures the density of edges within *Communities* (also called *Clusters*, *Provinces* or *Modules*) compared to the densities of *Communities* among themselves (Figure 2). CC quantifies the number of neighboring nodes that are interconnected to a specific node and quantifies local liquidity, while *Modularity* manifests the difference in intensity within *Communities* (intense) compared to the intensity of connection between *Communities* (sparse) (Gautam and Gupta, 2023). However, it has been shown that *Modularity* suffers from a resolution limit and is not efficient in detecting small *Communities* (Lancichinetti and Fortunato, 2011).

Regarding *Hubs*, they also present a great importance inside these *Communities*. Through the *Clustering Coefficient* (Van den Heuvel and Sporns 2013), it is possible to determine provincial *Hubs* (nodes that allow the integration of *Communities* with each other) or peripheral *Hubs* (nodes within the same *Community*, being fundamental within it).

Figure 2. *Clustering Coefficient* and *Modularity* (Gautam and Gupta, 2023).



The already mentioned ACN are present in the learning processes, such as in science and mathematics, in order to determine to what level of knowledge has been acquired (De la Hoz et al., 2024), being significant to understand the difficulties presented by students on some of these contents. It should be remembered that these studies emerge from the need to achieve a society with a greater capacity for critical development of basic knowledge, since an improvement in scientific and digital literacy is a priority (Nguyen et al., 2023). Despite this, there are studies (Porlán et al., 2010; Verdugo, Solaz and Sanjosé, 2019) that refer to the lack of scientific training of both students in compulsory stages and those of future initial education teachers.

At this stage, a scientific knowledge of current relevance is health and wellness, due to the growing concern about the increase in health problems, associated diseases and unhealthy lifestyle habits. In this sense, one of the most affected groups is university students, with unhealthy lifestyles, which affect their state of health during this age (García del Castillo et al., 2024). Previous studies have identified a characteristic pattern in the body composition of university students, which develops throughout this stage and tends to persist in later years. Notably, a significant increase in body mass has been observed in both males and females. This weight gain is primarily associated with physical inactivity and poor dietary habits, where the preference for snacks, fast food, and high-calorie products is driven by time constraints and personal preferences (Yaguachi et al., 2024).

Especially relevant is the problem of incorrect hydration, given the high intake of sugar-sweetened and energy drinks in the adolescent and youth population. To clarify that the recommendation for healthy hydration habits for a general adult population (WHO) is 2 liters per day, that is, 10 glasses of water (Aranceta et al., 2016; Martínez and Iglesias, 2006). Despite its importance, there is little research focused on scientific training and promotion of healthy hydration habits (Partida et al., 2018). An ideal scenario for this Health Education is still the school, where, in addition, technological and digital resources increase the effectiveness of such health promotion (De la Hoz et al., 2023; Durán-Vinagre et al., 2021).

It is clear that teacher training is essential to promote healthy lifestyles from the early stages. Previous studies (Molina-Márquez et al., 2024) indicate the need to include mandatory training programs on health education. This is fundamental, since the lack of scientific knowledge on health has been evidenced, especially in university students of careers outside specific professional training, such as Nutrition or Nursing (Luque and Molina, 2023). The study by Luque and Molina (2023) shows that university students in educational disciplines have the lowest scientific knowledge, especially male students. On the other hand, the study by Reyes-Narváez and Canto (2020) shows that engineering and social area students tend to have an unhealthy intake.

Thus, mentioning that the use and management of all these digital resources is undeniable in the training of prospective teachers, through innovative teaching in scientific, technical and digital literacy knowledge (Chai et al., 2020; Nguyen et al., 2023, De la Hoz et al., 2023), so it is necessary to advance in intervention programs, especially through cooperative methodologies and through the use of digital resources. The paradigm change is connected to the use of digital tools such as robotics or programming (Bocconi et al., 2022). In recent years, Educational Robotics (ER) has increased its inclusion in classrooms and in scientific literature. Several studies have demonstrated its positive impact on the development of skills such as Computational Thinking, critical thinking, problem solving, creativity and metacognitive skills (Bers, 2017), as well as learning in different areas, such as science and mathematics, and biosanitary content (Espinosa-Garamendi et al., 2022; Marcos-Pablo and García-Peñaldo, 2022). Despite this, there is very little scientific literature, especially of bioscience content (Belmonte et al., 2019; Marcos-Pablo and García-Peñaldo, 2022). For all these reasons, the innovative resource of Educational Robotics is presented as a possible alternative in the promotion of healthy lifestyle habits such as hydration (De la Hoz et al., 2023).

Therefore, the main aim of the present study is to analyze the Associative Cognition Networks in the learning of healthy hydration habits in pre-service teachers after an intervention based on Educational Robotics.

Method

The study adopted a pre-experimental design with a mixed analysis methodology (QUAL-quan), using qualitative category analysis and graph analysis, complemented by quantitative analysis using descriptive statistics (Creswel, 2014). The intervention was performed by convenience sampling with a total of 116 students and following the principles of the Declaration of Helsinki (World Medical Association, 2022). It should be noted that this research was approved by the Bioethics and Biosafety Committee.

Data collection procedure and instruments

Data collection was carried out after an intervention based on Educational Robotics, with the aim of promoting healthy hydration habits, through the learning of the most relevant biosanitary concepts of this habit. The objective was the creation (through collaborative groups of 4 students) of robotic boards to teach healthy hydration habits, in addition to reports that would include images, descriptions and other resources necessary to guide on how to use the robotic board in an educational classroom.

The intervention was implemented using the Mind Designer® robotics kit for 5 one-hour sessions, allowing students to learn the basics of using ER resources and programming in the elementary educational stages. During the first 3 sessions, pre-service teachers were instructed on the functionality of the robotic boards, specifically on scientific and mathematical content (UNESCO, 2016), allowing students to understand and reflect on the variety of options that can be employed for their use in the classroom. This intervention continued with 2 practical sessions to carry out the proposed project. In these sessions, students were guided in the search, analysis and use of biosanitary contents, through specialized health websites or platforms, such as the *WHO*, *MedlinePlus*, *Healhfinder* and bibliographic bases such as *Dialnet*, *PubMed* or *ERIC*. It should be clarified that the websites specialized in health had to have the Seal of Quality in Digital Health: *Health On Net Foundation* (HON), which guarantees their scientific and biosanitary rigor, providing students with resources to improve their Digital Health Literacy (De la Hoz et al., 2021).

Data were obtained from these boards and reports, using qualitative analysis through a previously employed category system (Table 1) (De la Hoz et al., 2023). WebQDA® software (Costa et al., 2016) was used for the analysis. Subsequently, the proximity relationship was identified through the frequency of co-occurrence of the subcategories, by the number of times that two or more categories appear in the same text (Pérez-Vera et al., 2024). It should be clarified that it is not enough just to appear in the same grammatical sentence, but it is necessary to establish a connection with scientific rigor, so that there is a scientific relationship of the associated terms.

Table 1. Category system for the analysis of the scientific knowledge of hydration (De la Hoz et al., 2023)

Scientific Knowledge	Main Dimension	Categories	Subcategories
Scientific Knowledge Hydration	Water	Number of glasses	10 glasses
			6 glasses
		Hydration volume	2 L
			200–250 mL
	Other drinks	Healthy drinks	Milk
			Natural juice
			Tea and infusions
			Gazpachos
			Lemonade natural
		Unhealthy drinks	Sweetened soft drinks
			Sugared juice/milkshake
			Energy drinks

Network analysis

Based on triangular matrix of the frequency data collected with the qualitative analysis using WebQDA®, an analysis of different ACN was conducted. Three independent networks were generated. First, a general ACN of the scientific knowledge acquired by the students was obtained, in order to determine the relationships between the different knowledge acquired. Subsequently, two different ACN have been obtained, attending, on the one hand, to a fundamental parameter of network analysis, and on the other hand, to the scientific foundation on a content of relevance within healthy hydration habits. Therefore, a second ACN has been obtained with respect to the main *Hub*, based on the data obtained only by those students who had acquired scientific knowledge of that specific bioscientific content. Finally, a third network has been obtained from the data obtained only by those students who had acquired the scientific knowledge of daily intake of *2 liters of water* as recommended consumption (Aranceta et al., 2016; Martínez and Iglesias, 2006) and, therefore, with healthy hydration habit.

In these undirected networks, the connections show the co-occurrence of the nodes, so that the edges density represents the *Strength* (*Weight*) of the relationship, equivalent to the total number of occasions in which two nodes are connected (Chang and Tsai, 2023; Fernández-Batanero et al., 2021). On the other hand, the size of the nodes is represented as a function of the *Degree* of each node. Moreover, for the analysis and representation of graphs, the different scales (macro-level, meso-level and micro-level) and their fundamental metrics have been considered, such as:

Degree (Q): a node of high *Degree* has many closely related neighbors, while of low *Degree* has few. By means of this parameter, the *Hub* of each ACN, corresponding to the node with the highest Degree, is obtained.

General and *Local Clustering Coefficient* (CC): ratio of the connections between its neighboring nodes; this is acquired by the number of closed triangles in relation to the total number of possible triangles.

Average Shortest Path Length (ASPL): which quantifies the *Average Shortest Path Length* between all possible pairs of nodes.

Modularity (Q): measures the density of edges within *Communities* (also called *Clusters*, *Provinces* or *Modules*) compared to the densities of *Communities* among themselves.

Gephi® and Cytoscape® software were used for this graph analysis. The final representation and visualization were carried out in Gephi®, applying the *ForceAtlas2* algorithm (González-Bustamante and Cisternas, 2020; Jacomy et al., 2014). This algorithm is based on repulsion, attraction and gravity formulations. The attraction equation is expressed as follows:

$$F_{\alpha}(n_1, n_2) = \log(1 + d(n_1, n_2))$$

The repulsion considers the Degree of the nodes based on a count of the connected edges; its equation is as follows:

$$F_r\,(n_1, n_2) = k_r \frac{(\deg(n_1) + 1)\,(deg(n_2 + 1)}{d(n_1, n_2)}$$

In addition, the gravity effect is employed to prevent disconnection of isolated components, by the equation:

$$F_g = k_g(\deg(n) + 1)$$

Results

Following, the different ACN are presented, beginning with the general graph of scientific knowledge, after the intervention with Educational Robotics, and followed by the ACN related to the main *Hub* of the ACN and, finally, the ACN related to the scientific knowledge of *2 liters of water*, given that it is the recommended daily consumption (Aranceta et al., 2016; Martínez and Iglesias, 2006) and, therefore, fundamental in the habit of healthy hydration.

To clarify that, attending to the results of the meso-level scale (Table 2), *Modularity* does not present determinant value for the detection of *Communities*, because of the limitations provided by the parameter (Lancichinetti and Fortunato, 2011). Therefore, the resolution of *Modularity* was adjusted to 0.8 for the detection of *Communities* (*Cluster*, *Province* or *Module*). Table 1 presents the metrics corresponding to the macro-level scale of each ACN.

Table 2. Metrics of the macro-level scale of each Associative Cognition Networks.

	Macro-level scale		
ACN	Average Degree	Clustering Coefficient Global	ASPL
General	148	0.924	1
Main Hub	147.17	0.924	1
2 liters of water	134.33	0.924	1

Thus, with regard to the ASPL, all the networks have a value of 1, as does the *Global Clustering Coefficient*, with a value of 0.924. As for the value of the average *Degree*, there are differences, being higher in the general ACN (148), followed by the ACN related to the Main *Hub* with 147.17 and the ACN of *2 liters of water* with 134.33.

Figure 3 shows the general *Associative Cognition Networks* on the bioscientific knowledge of healthy hydration habits, after the Educational Robotics intervention, as well as the metrics corresponding to the micro-level scale of its nodes (Table 3).

Figure 3. Overall ACN on bioscientific knowledge of healthy hydration.

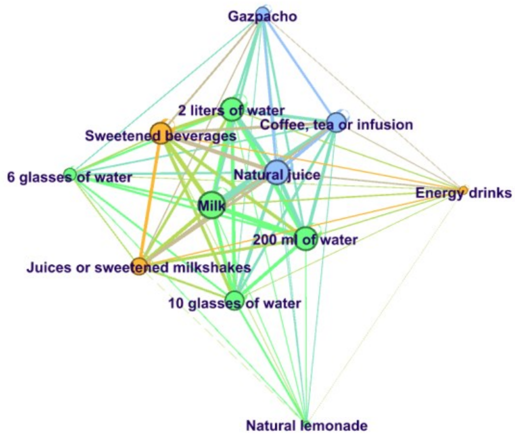


Table 3. Overall ACN micro-level scale metrics on bioscientific knowledge of healthy hydration.

Nodes	Micro-level scale		
	Degree	Local Clustering Coefficient	Community (Cluster)
10 glasses of water	156	0.83	1
6 glasses of water	105	0.83	1
2 liters of water	188	0.83	1
200 ml of water	191	0.95	1
Milk	217	0.95	1
Natural juice	198	0.95	2
Gazpacho	114	0.95	2
Natural lemonade	61	0.95	1
Coffee, tea or infusion	160	0.95	2
Sweetened beverages	175	0.95	3
Juices or sweetened milkshakes	140	0.95	3
Energy drinks	71	0.95	3

As can be seen, the nodes with the highest *Degree*, such as *Milk* (217), *Natural juice* (198), *2 liters of water* (188), *200 ml of water* (191) or *Sweetened beverages* (175), are in the center of the network. On the other hand, those with lower *Degrees*, such as *Natural lemonade* (61) or *Energy drinks* (71) are situated further away. In this case, the *Hub* (node with the highest *Degree*) would be *Milk* (*Degree*= 217). In addition, through the *Modularity* (Q=|0.039|), the graphs of 3 different *Communities* (*Cluster*) can be appreciated. On the one hand, there is the *Community* (*Cluster* 1) with the nodes 10 glasses of water, 6 glasses of water, 2 liters of water, 200 ml of water, Milk and Natural lemonade; the Community (*Cluster* 2) presents the nodes N*atural juice, Gazpacho and Coffee, tea or infusion*; finally, the *Community* (*Cluster* 3) presents the nodes *Sweetened beverages, Juices or sweetened milkshakes* and *Energy drinks.*

In view of these results, the *Hub* of the general ACN (*Milk*) has been used to obtain the second ACN. Therefore, only the data relating to students who had acquired adequate scientific knowledge of this bioscience content were used. Based on this, the RAC relative to the *Hub* (*Milk*) can be observed in Figure 4. In addition, Table 4 shows the metrics corresponding to the micro-level scale of its nodes.

Figure 4. ACN relative to the *Hub* (*Milk*).

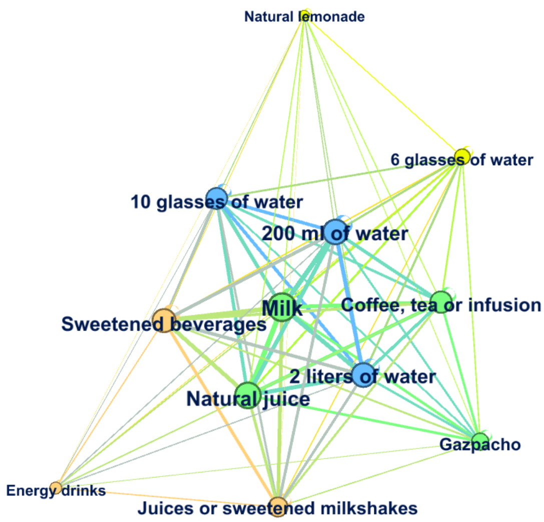


Table 4. Metrics of the micro-level scale of the ACN relative to the Hub (Milk).

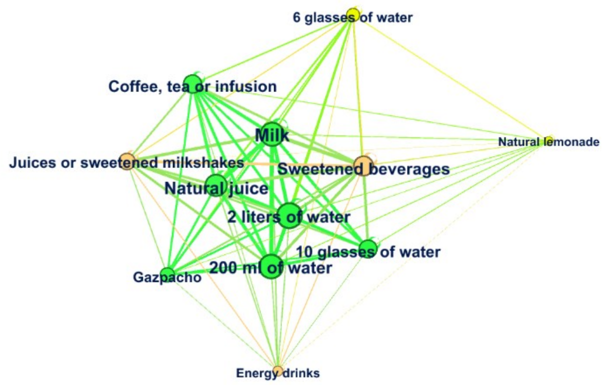
Nodes	Micro-level scale		
	Degree	Local Clustering Coefficient	Community (Cluster)
10 glasses of water	156	0.83	1
6 glasses of water	105	0.83	2
2 liters of water	181	0.83	1
200 ml of water	188	0.95	1
Milk	217	0.95	4
Natural juice	198	0.95	4
Gazpacho	114	0.95	4
Natural lemonade	57	0.95	2
Coffee, tea or infusion	160	0.95	4
Sweetened beverages	175	0.95	3
Juices or sweetened milkshakes	140	0.95	3
Energy drinks	71	0.95	3

In the same way, the nodes with higher *Degree*, such as *Milk* (217), *Natural juice* (198), *2 liters of water* (181), *200 ml of water* (188) or *Sweetened beverages* (175), are in the center of the network. On the other hand, those with lower *Degree*, such as *Natural lemonade* (61) or *Energy drinks* (71) are further away. In this case, the *Hub* (node with the highest *Degree*) would be *Milk* (*Degree*= 217). Thanks to the *Modularity* (Q=|0.05|), 4 different *Communities* (*Clusters*) can be appreciated. On the one hand, there is the *Community* (*Cluster* 1) with the nodes *10 glasses of water, 2 liters of water* and *200 ml of water*; the *Community* (*Cluster* 2) presents the nodes *6 glasses of water* and *Natural lemonade*; the *Community* (*Cluster* 3) presents the nodes *Sweetened beverages*, *Juices or sweetened milkshakes* and *Energy drinks*; finally, the *Community* (*Cluster* 4) groups the nodes are *Milk*, *Natural juice*, *Gazpacho* and *Coffee, tea or infusion.* Finally, the ACN as a function of knowledge of node *2 liters of water* are presented (Figure 5), as well as the micro-level scale metrics of their corresponding nodes (Table 5).

Table 5. Metrics of the micro-level scale of the ACN related to the bioscientific knowledge of 2 liters of water.

Nodes	Micro-level scale		
	Degree	Local Clustering Coefficient	Community (Cluster)
10 glasses of water	149	0.83	1
6 glasses of water	105	0.83	2
2 liters of water	188	0.83	1
200 ml of water	176	0.95	1
Milk	181	0.95	1
Natural juice	174	0.95	1
Gazpacho	111	0.95	1
Natural lemonade	57	0.95	2
Coffee, tea or infusion	141	0.95	1
Sweetened beverages	147	0.95	3
Juices or sweetened milkshakes	118	0.95	3
Energy drinks	65	0.95	3

Figure 5. ACN relative to bioscientific knowledge of 2 liters of water.



In this ACN, the highest *Degree* nodes, located more centrally, are *2 liters of water* (188), *Milk* (181), *200 ml of water* (176), *Natural juice* (174), while the lowest *Degree* nodes, farther away, are *Natural lemonade* (57) and *Energy drinks* (65). In this case, the *Hub* (highest *Degree* node) is the node *2 liters of water* (*Degree*=188). As for *Modularity* (Q=|0.058|), 3 different *Communities* (*Clusters*) can be appreciated. On the one hand, there is the *Community* (*Cluster* 1) with the nodes *10 glasses of water, 2 liters of water, 200 ml of water, Milk, Natural juice, Gazpacho* and *Coffee, tea or infusion*; the *Community* (*Cluster* 2) presents the nodes *6 glasses of water* and *Natural lemonade*; finally, the *Community* (*Cluster* 3) groups the nodes *Sweetened beverages*, *Juices or sweetened milkshakes* and *Energy drinks*.

Discussion

Advances in Neurocognition and Neuroeducation emphasize the need to improve how student learning is analyzed, particularly in understanding how students structure and connect knowledge (Mora, 2021). Researchers have turned to cognitive network science to explore how students organize knowledge, offering a complementary approach to traditional assessments (Correa-Bautista et al., 2024; Luchini et al., 2024). *Associative Cognition Networks* (ACN) provide insights into the challenges of learning scientific content and how this knowledge interrelates during the learning process (De la Hoz et al., 2024). The use of network analysis in education aligns with neuroeducational principles, allowing for a more detailed examination of cognitive structures and how learning occurs dynamically over time, supporting the view that the way students structure their knowledge is strongly influenced by neurocognitive mechanisms (Mora, 2021).

Health education from early stages requires that pre-service teachers develop strong scientific and digital literacy to promote healthy habits (Cubero et al., 2019). Digital tools, like Educational Robotics, play a crucial role in this learning process (Bers, 2017). This study analyzes pre-service teachers' knowledge structures using ACN to assess relationships formed during learning, as previous research has shown (Huie et al., 2022; Jones et al., 2014; Luchini et al., 2024; Qin, Li, & Yang, 2024), following a didactic intervention with Educational Robotics. In this line, the study analyze how the integration of Educational Robotics influences neural learning pathways and knowledge networks among students.

Observing the layout of the nodes in the three ACN, it was observed that the most central and the most external nodes coincide in their placement. The central nodes correspond to those with the highest *Degree* in each ACN (micro-level scale), while those farthest from the center have a lower *Degree*. The nodes with highest *Degree* are *Milk*, *Natural juice*, *200 ml of water, 2 liters of water* and *Sweetened beverages*, while the nodes with lowest are *Natural lemonade* and *Energy drink.* These structural differences align with findings in neuroeducation, which suggest that stronger conceptual connections (i.e., higher Degree nodes) indicate better consolidation of knowledge.

The analysis of the *Degree* shows that *Milk* is the *Hub* (highest *Degree*) in the overall ACN on bioscientific knowledge of healthy hydration (*Degree*=217). This coincides with the specific ACN of those students who acquired deeper knowledge of this bioscience content, a result also observed in previous studies on fluid intake in similar populations, where milk consumption is associated with adequate hydration habits (Iglesia et al., 2016). Neuroeducational research has shown that *Hubs* in cognitive networks play a crucial role in facilitating knowledge retrieval and application, suggesting that the concept of *Milk* as a central hydration source is well-integrated into students' cognitive schemas (Van den Heuvel & Sporns, 2013). Thus, the role of educational robotics can be linked to brain plasticity in response to novel input and active learning experiences, where interactions with physical robots create new neural pathways that enhance knowledge retention and integration.

Comparing the *Degree* of other nodes (Table 4) with the overall ACN (Table 3), it is observed that most of them coincide, except for *2 liters of water* (from 188 to 181), *200 ml of water* (from 191 to 188) and *Natural lemonade* (from 61 to 57), whose *Degree* slightly decrease in the ACN relative to the main *Hub* (*Milk*). This variation is also reflected in the macro-level scale (Table 2), where the average *Degree* of the overall ACN is 148, while in the ACN relative to the main *Hub* (*Milk*) it is slightly lower, with an average of 147.17.

Regarding the *2 liters of water* bioscientific knowledge ACN, the *Hub* (highest *Degree*) corresponds with the *2 liters of water* node (*Degree*=188). Similarly, the nodes of higher and lower *Degree*, as well as their layout, coincide with the previous ones, except for the *2 liters of water* node, which is also disposed as a *Hub*. As for differences, the node *10 glasses of water* present a higher *Degree* (149) than the nodes *Sweetened beverages* (147) and *Coffee, tea or infusion* (141), while in the previous ACN it presented a lower *Degree*. Furthermore, looking at the results of the macro-level scale (Table 2), the average *Degree* of this ACN is the lowest, with 134.44. This reflects a greater understanding of the concept of recommended daily intake volume compared to the number of specific glasses.

In view of these results, it is concluded that the scientific knowledge acquired by the pre-service teachers after the intervention with Educational Robotics is focused on relevant contents on the habit of healthy hydration. Previous studies (Aranceta, 2016; Martínez and Iglesias, 2006) indicate that the main objective of an effective Health Education is to understand the importance of daily water intake, represented by the consumption of 2 liters of water.

In addition, the ACN on the *2 liters of water* highlights the node *10 glasses of water*, suggesting that pre-service teachers have a better understanding of the recommended volume than the daily amount of glasses. However, those who understood the concept of volume correctly also established a strong relationship with the recommended number of glasses, indicating more comprehensive learning. Similarly, the node *6 glasses of water* presents a lower importance in all ACN. These results may be due to the fact that some quality educational resources used to work on hydration content, such as the *Healthy Eating Pyramid* or the *Healthy Plate* (Aranceta et al., 2016; Harvard School of Public Health, 2024; Martinez and Iglesias, 2006), make more reference to the adequate amount of consumption and not so much to the minimum amount. Thus, more emphasis is placed on the total recommended volume of intake than on the minimum, so more emphasis needs to be placed on this content, of minimum volume, in subsequent studies.

Regarding healthy beverages, the nodes with the highest *Degree* and centrality (*Milk* and *Natural juices*) correspond to the beverages with the highest consumption in children and youth ages (Aranceta et al., 2016; Nissensohn et al., 2016). Pre-service teachers demonstrate a relevant level of knowledge in these beverages, adequate for the educational stage they are targeting. Concerning unhealthy beverages, the *Sweetened beverages* node highlights as the main unhealthy beverage, in line with studies that report its problematic high intake in children and young people (Poulos and Pasch, 2016; Mayo and Izquierdo, 2019). The pre-service teachers show a good knowledge about the problematic of these beverages on health, suggesting that the intervention with Educational Robotics is effective in teaching these concepts.

According to the meso-level, the *Associative Cognition Networks* show that the *Community* (*Cluster* 3) groups the various unhealthy beverages, with *Sweetened beverages* as the main node. This indicates that the pre-service teachers correctly differentiate between healthy and unhealthy beverages and understand their properties. As for healthy beverages, they appear in separate *Communities* from unhealthy beverages. In addition, a connection between healthy beverages and water is also evident, especially through the *Milk* node, placing it in the same *Community* as the nodes associated with water intake (Figure 3 and 5). This may be due to the frequency of intake of both beverages, due to the fact that pre-service teachers associate the beverages that should be ingested on a daily basis, as guides and scientific studies have reflected, due to their importance in the healthy hydration habit, especially at early ages (Aranceta, 2016; Martínez and Iglesias, 2006; Mayo and Izquierdo, 2019; Nissensohn et al., 2016; Poulos and Pasch, 2016).

The results of the study show that pre-service teachers present a positive level of science knowledge after the intervention, similarly to other studies (Cubero et al., 2019; Franco-Reynolds et al., 2022; Steven, Wilson and Young-Murphy, 2019), which implemented active interventions and were based on digital literacy for health. Additionally, this coincides with recent studies (Fussero and Occelli, 2022; Ntourou, Kalogiannakis and Psycharis, 2021), which have reflected an improvement in scientific knowledge after that of interventions with the use of Educational Robotics, especially in university students of *Degree* in Education (Román-Graván et al., 2020; Schina et al., 2020), and especially with contents related to water (Puškar et al., 2023), which has an implication on the inclusion of this valuable resource as suitable at any educational stage for the formation of scientific knowledge. Therefore, the introduction of these digital resources should be increased in teaching programs. The structuring of hydration-related concepts suggests that pre-service teachers have successfully integrated essential information, highlighting the role of structured learning experiences in strengthening neural pathways associated with health knowledge.

This coincides with previous studies (Nissensohn et al., 2015) that have exposed the need for integral learning of these contents. In view of these results, the intervention based on Educational Robotics seems to be a useful tool in the fight against the alarming public health situation of childhood and juvenile obesity.

To conclude, the analysis of the ACN has allowed us to analyze the concepts (nodes) of higher learning, complemented by a correct association of concepts, properly differentiating between healthy and unhealthy beverages, and establishing a close relationship between water intake and healthy beverages, especially *Milk*. Therefore, the study of ACN is presented as a proper analysis methodology to evaluate and assessment the learning of bioscientific content, as studies have shown in scientific content (Chang and Tsai, 2023; Luchini et al., 2024; Siew, 2020), and especially through the use of software such as Gephi in the analysis of scientific content (De la Hoz et al., 2024; Huie et al., 2022; Qin, Li and Yang, 2024). Furthermore, Neuroeducational perspectives confirm the validity of network-based approaches in assessing learning by providing insights into the interconnectedness and consolidation of knowledge structures in the brain (Stella, 2022). The results align with the principles of neuroeducation, which emphasize neural plasticity and the consolidation of knowledge through active, multisensory learning experiences, such as those offered by Educational Robotics. Clearly, further research is needed to explore the value of cognitive networks to determine their effectiveness and efficiency compared to other assessment approaches (Correa-Bautista et al., 2024; Jones et al., 2014).

Conclusions

Neurocognitive and neuroeducational approaches highlight the need to deepen students' learning by exploring how students organize knowledge using the cognitive network science, which offers a viable, valid, and complementary approach to traditional educational assessments.

The study highlights the use of *Associative Cognition Networks* (ACN) as a method for the evaluation and assessment of science content learning, particularly on healthy hydration habits. The ACN allowed identifying how pre-service teachers structure and connect content of great scientific value, revealing consolidated knowledge patterns in key concepts such as *Milk* and *Natural juice*, correctly differentiating between healthy and unhealthy beverages, and better understanding the recommended volume of daily water intake than the number of glasses.

The Educational Robotics intervention emerged as an effective tool for enhancing scientific and digital literacy, fostering a more holistic learning experience in key health-related topics. This aligns with neuroeducational principles, demonstrating how hands-on, interactive learning technologies can strengthen cognitive structures and improve conceptual retention. These findings are consistent with previous studies that emphasize the relevance of these competencies in Higher Education.

Therefore, this study reinforces the role of ACN and Educational Robotics as powerful assets in Higher Education, not only in the teaching of scientific content, but also as tools for digital literacy and underlining the need to continue with specific educational interventions to improve bioscientific knowledge for Education and Health Promotion and wellness.

Limitations of the study and future lines of research

The study has certain limitations. First, it shows a low level of *Modularity*. Although there are studies (Marcelo-García and Marcelo-Martínez, 2021) that show the value of a network analysis at low values of *Modularity*, numerous studies that complement the results found would be ideal.

In the same way, it is convenient future research that performs a network analysis both before and after the intervention, expanding the study sample, and on different contents and contexts, in order to increase the use of this methodology as an alternative for learning assessment**.**

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Ethical statement

The study was conducted in accordance with the Declaration of Helsinki. Ethic Committee Name: The Bioethics and Biosafety Committee of the University of Extremadura; Approval Code: 139//2023; Approval Date: November 2023.

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Declaration of interest statement

The authors report there are no competing interests to declare.

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