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Neuroeducation in the Learning of Linear Programming Models in the Systems Engineering Career

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Abstract– In Systems Engineering, the subject of Operations Research requires as a basis the Construction of Linear Programming Models. The aim of this research was to find the effect of neuroeducation in the construction of these models. It was an applied study of explanatory scope, of quasi-experimental design with 60 students (control group) and 60 students (experimental group). The data collection instrument was an evaluation rubric based on the stages of the construction of the models, being validated by experts and with a Cronbach reliability of 0.8. Neurodidactic strategies were applied for the integrated activation of higher cognition devices (attention, memory, motivation, and emotion). A p value of 0.00 was obtained with Mann Whitney U, so it was concluded that the use of neuroeducation strategies was significant, obtaining a better construction of linear programming models.

Keywords-- Neuroeducation, Didactics, Linear Programming, Model Mathematical

I. INTRODUCTION

Engineering students demand innovative educational systems as well as university teaching that motivate learning and meaningful learning achievements. The subject of operations research as part of the basic training of the Systems Engineering career uses a certain complexity and abstraction in the construction of mathematical models that reflect the problems to be improved.

Linear programming (LP) uses models of linear functions based on alternatives for some problem that requires deciding; a model is composed of variables, optimization goal and constraints that must be met. The university problems found report difficulties in the construction of LP models, since they are elaborated with deficiency, and by wanting to respond to these formulations with errors, results and failed decisions will also be obtained. University classes in engineering have still been stationary with traditional teaching strategies despite relying on ICT (Information and Communication Technologies).

Neurodidactics is an interdisciplinary field related to neuroscience, pedagogy, psychology, and others, which seeks to contribute to active learning taking into account the functioning and activation of the brain [1]. Mora [2], regarding learning, indicated "It is not only about promoting emotions in class, it is about teaching with emotion, by making what is taught different and curious, by turning any element into something interesting and by automatically awakening attention to learn better".

Talking about learning requires identifying the foundations of the acquisition of new knowledge, the conceptions of its construction and interaction with previous knowledge, therefore, it seeks to analyze the theory of constructivism that Ausubel postulates within the university context. Engineering students build their learning and understanding, they are active learners through their own development and structuring, with the use of some techniques and materials applicable either individually or collectively. This construction of learning will depend to a large extent on the learning process in which they are involved by their training, considering their capacity at the level of abstraction and logical thinking [3], [4].

Neuroscience seeks to improve learning behaviors to generate conditions for better performance based on positive emotions [5]. Learning with stable emotions becomes a process that motivates and cheers [6]; therefore, learning with emotion has become a requirement in neurodidactics, since it allows students to be involved in active collaboration. Somehow, Polya was already looking for mathematics to become popular and meaningful, pointing out the need to learn pleasantly and with pleasure, remembering that the objective is the solution of problems from ingenuity and creativity [7].

It is important not to lose sight of the goal of university learning: the achievement of competences and skills, evidenced in the learning outcomes in each subject of the curriculum, and neurodidactics is an option that allows motivating young people in their training process. Building a mathematical model requires a high level of analysis due to the variety of cases and applications [8], building it correctly requires a set of systematic steps.

As theoretical references, Valdivieso et al. [9], since his research in the university environment obtained a correlation of 0.04 between the mental structure and the application of neurodidactics in university students. Otherwise, Díaz et al. [10] and Al-Balushi and Al-Balushi [11], studied brain-based learning and its influence on retaining students in engineering, where the experimental group gained a 6% advantage over the control group. Similarly, Ballesta-Claver et al.[12], were able to identify those strategies based on neuroeducation to sensitize, attend and cooperate in active learning, with critical and meaningful thinking, improving from 64% to 73% in performance. Vigo [13] designed a neurodidactic model based on the systems approach, reaching 64% improvement in performance. Also, Tacca et al. [14] found a positive correlation with 0.72 for neurodidactics with performance.

The study in emotional self-regulation of Plaza et al. [15] analyzed the principles of neurodidactics along with learning styles for mathematics, to counteract anxiety and demotivation. It was concluded that the teacher is the one who must be trained and updated according to the requirements that require learning with novelty, and from the interests, attitudes, and participation in a good environment.

In a new university context in Systems Engineering requires the validation of strategies that help improve learning for better performance, so, the aim of this research was to find the effect of neuroeducation in the construction of linear programming models in the subjects of Operations Research.

II. Method

A quantitative approach was used, with explanatory scope and with applied research of quasi-experimental design with pre and posttest, with control and experimental group, with a sample population of 60 students for each group; the technique used was structured observation with the rubric instrument built from the phases of the construction of linear programming models. The instrument was validated by experts and presented a reliability of Cronbach's alpha equal to 0.8, acceptable [16]. Descriptive and inferential statistics were used for the treatment and analysis of results.

Normality was evaluated with the Kolmogorov Smirnov test, for samples less than 50, obtaining a non-normal distribution, so Mann-Whitney U was selected [17]**.** The dependent variable Construction of LP models was operationalized for measurement following the sequence of flows of the methodology for its design, as shown in Fig. 1 [18], with these stages, the evaluation rubric was built (Fig.2).

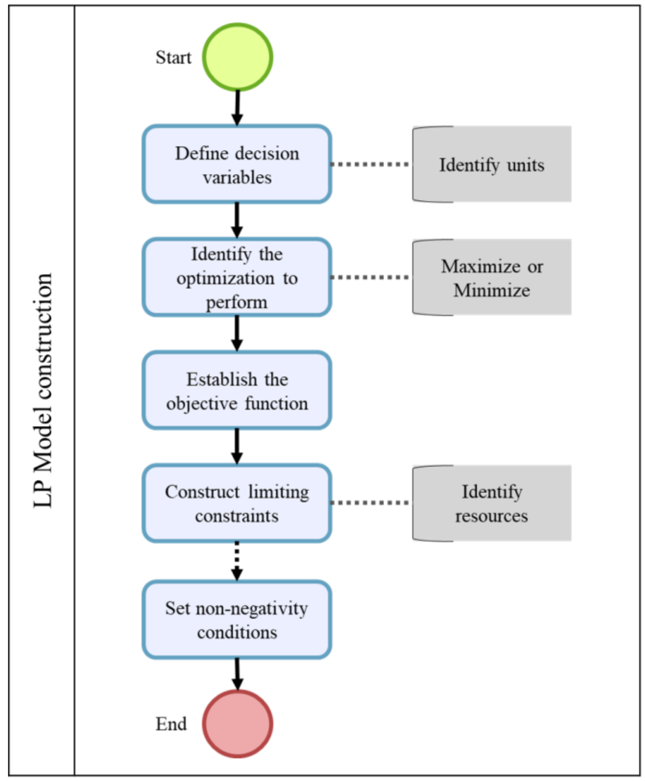

Fig. 1. Phases for the Construction of Linear Programming Models

Assessment Rubric: Building a Linear Programming (LP) Model

RESULT / CATEGORY	Well (4)	Regular (2)	Deficient (1)	Null (0)
Identifying Variables	All variables in the model are correctly identified.	50% of all variables in the model are correctly identified.	All variables in the model are identified incorrectly.	Model variables are not identified.
Defining Variables	The decision variables are defined considering the name, the unit of measurement and the description of the problem.	Decision variables are defined considering the name and description of the problem.	Decision variables are defined based on name only.	Model variables are not defined.
Definition of objective function	The objective (max/min) is correctly defined, and the corresponding coefficients of the linear function are associated.	The objective (max/min) is correctly defined, and the corresponding coefficients of the linear function are associated by 50%.	The objective and coefficients of the linear function are defined incorrectly.	The objective function is not defined.
Identification and definition of constraints	All constraints are correctly identified and defined as inequalities.	50% of constraints are correctly identified and defined as inequalities.	Constraints are incorrectly defined as inequalities.	Model constraints are not defined.
Obtaining the LP Model	The mathematical model is obtained, without errors or omissions.	The mathematical model with omissions is obtained.	The mathematical model with errors is obtained.	It is not possible to obtain a mathematical model.

Fig. 2. Rubric for the Evaluation

As can be seen, the evaluation is divided into 5 categories (stages of the method), with scores from 1 to 4 maximum, making up a total of 20 points in the national university system; these measurements were considered for the evaluation of the pre and posttest.

Ausubel [3] differentiates two types of learning for the university classroom, a dimension in the way in which knowledge is acquired and the dimension of the way in which knowledge is incorporated into the cognitive structure of the young student. In the first dimension there are two possible types of learning, by reception and by discovery, while in the second dimension there are two modalities, by repetition and meaningful. Meaningful learning is only a first stage in the assimilation of learning, after which retention and forgetting or gradual reduction are found as natural sequelae. In retention, new meanings are organized in memory by linking with its most stable anchoring ideas, updating themselves, through repetition or rehearsal. Cognitive and social variables related to motivation influence significant retention or, on the contrary, forgetting is favored with repression or learning shock.

In this sense, the neurodidactic strategies used as a stimulus for the experiment of integrated activation of higher cognition devices such as attention, memory, motivation and emotion, are shown in Fig. 3, which were applied alternately in different activities such as: the reception of students to class, mental relaxation, recovery of previous knowledge, the active breaks during the session, the elaboration of groups proposal, the consolidation of what has been learned in each session and the extra class activities of individual and group complementation.

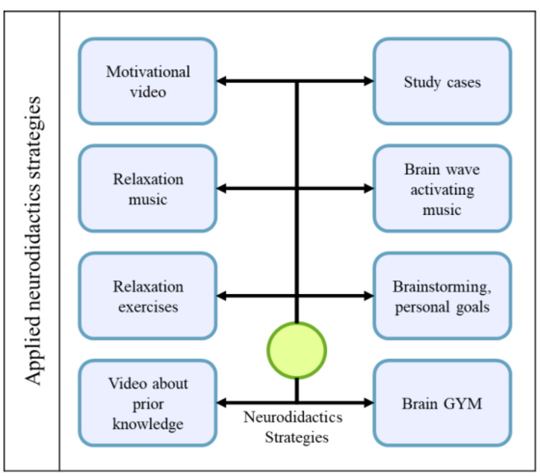

Fig. 3. Neuroeducation strategies used

Thoughts behave in a certain way during learning, related to the activation processes of the brain, the areas of learning and the context that is lived during personal experience. This research took into account the modes of thinking described by Oakley[19], the concentrated mode and the diffuse mode, the learner is either in one or the other, changing frequently; in diffuse mode you can work in silent mode and without triggering attention; the concentrated mode is required for the learning of mathematics and university sciences, related to the analysis and solution of problems, which requires the capacity of attention for its activation; the fuzzy mode also participates in the study of mathematics, and helps to look for a new vision after struggling in the solution of a problem of high level of abstraction, since sometimes it is necessary to relax the attention to let the mind act, by allowing some areas of the brain to make a connection to find alternative answers that when being intensely concentrated can use erroneous thoughts; the fuzzy mode includes an overview, this mode is useful in new learning, as it does not allow you to concentrate much when looking for an uncluttered route. The concentrated mode is used when you are already familiar with professional knowledge because it follows a path that you already know and practice.

The nature of systems engineering students is characterized by concentration on the programming or coding activity, by proving a very dedicated time in concentrated mode, and makes it more difficult to adopt the relaxed fuzzy mode. Some fuzzy mode triggers to look out for young engineering students are doing physical activity, driving or taking a walk, doing an art activity, taking a shower, listening to instrumental music, meditating, or sleeping.

As a verification measure, there were two posttests, the first one (posttest 1) evaluated the same examen from de pretest, while the second one (posttest 2) evaluated a new examen with another contents, all the exams were evaluated with the same rubric for the construction of the linear programming model (instrument).

III. Results and discussion

For the dependent variable Construction of linear programming (LP) models, Fig. 4 details similar averages in the pretest with a median of 6 for both groups, which presented a disapproving and low vigesimal evaluation.

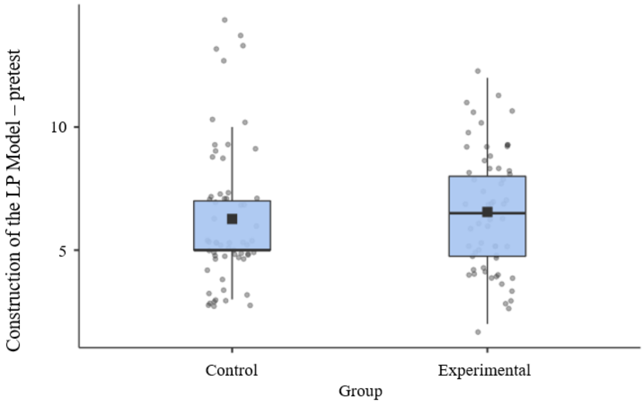

Fig. 4. Construction of the LP Model (pretest) Box diagram

In posttest 1, with the application of neurodidactic strategies, medians of 16 (control group) and 20 (experimental group) were found (Fig. 5), seeing that the evaluations were higher in the experimental group.

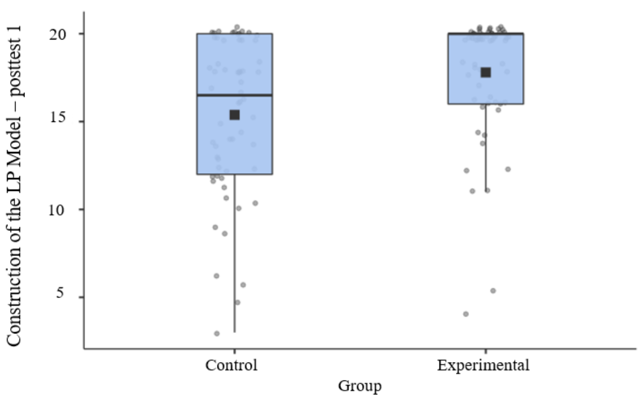

Fig. 5. Construction of the LP model (posttest 1) Box diagram

In posttest 2, medians of 14 (control group) and 17 (experimental group) were found (Fig. 6), again seeing that the evaluation of the experimental group was superior to the control group.

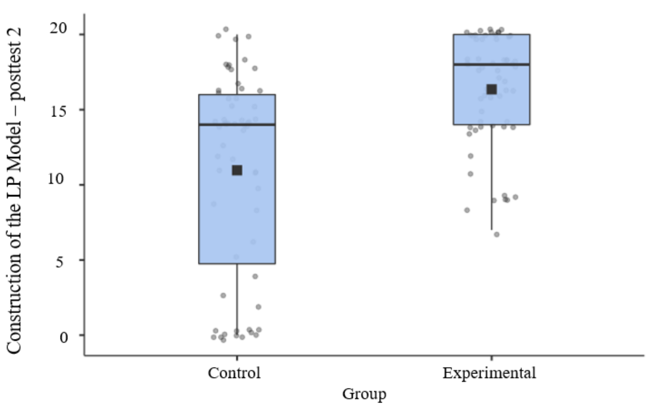

Fig. 6. Construction of the LP model (posttest 2) Box diagram

Then, considering the detailed evaluation by dimensions, in phase 1: Identification of variables, Fig. 7 details similar results in the pretest, with a median of 2 for both groups.

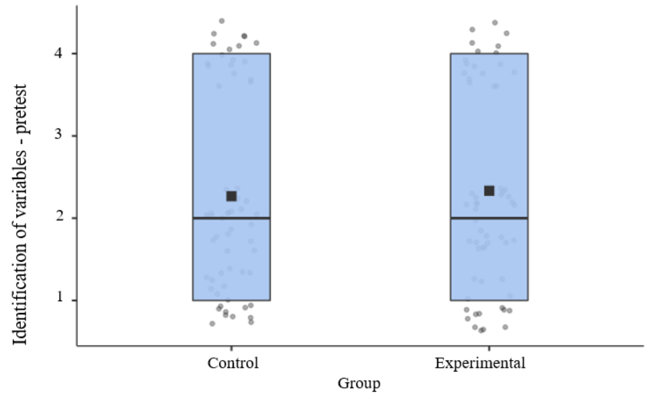

Fig. 7. Dimension 1 - Identification of variables (pretest) Box diagram

In posttest 1 and posttest 2, the dimension: Identification of Variables, obtained medians of 4 for both groups (Fig.8 and 9), however in posttest 2 a difference in the proportion of frequencies is seen, leaving the experimental group in a higher position.

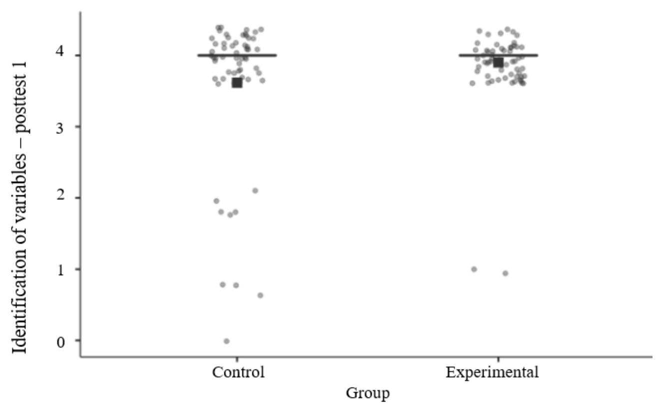

Fig. 8. Dimension 1 - Identification of variables (posttest 1) Box diagram

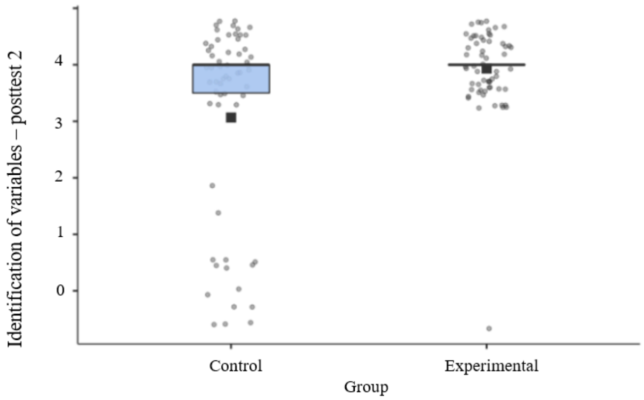

Fig. 9. Dimension 1 - Identification of variables (posttest 2) Box diagram

In phase 2: Definition of variables, Fig. 10 details similar results in the pretest, with a median of 2 for both groups.

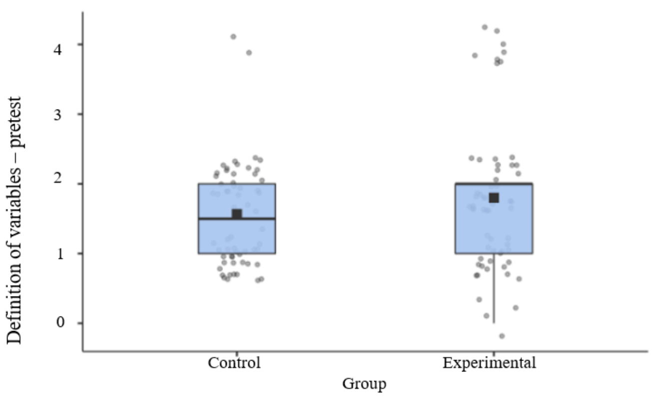

Fig. 10. Dimension 2 - Definition of variables (pretest) Box diagram

In the posttest 1 and in the posttest 2, the dimension: Definition of Variables, obtained medians of 4 for both groups (Fig. 11 and 12), however in both distributions a difference in the proportion of frequencies is seen, leaving the experimental group in a superior position.

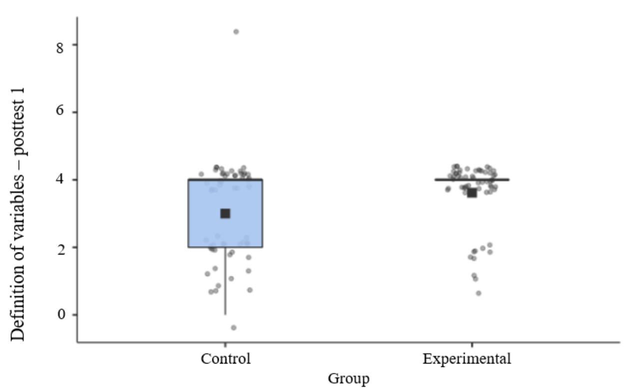

Fig. 11. Dimension 2 - Definition of variables (posttest 1) Box diagram

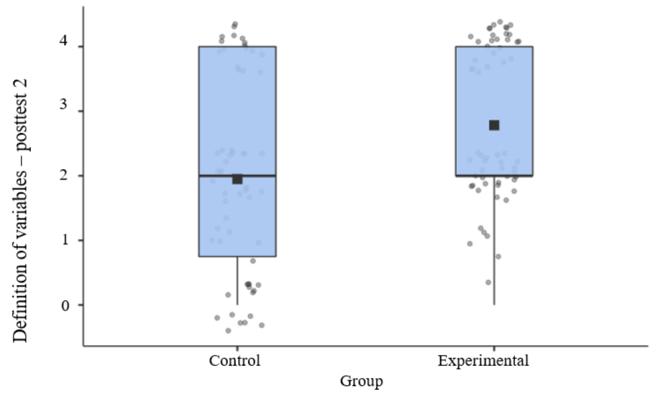

Fig. 12. – Dimension 2 - Definition of variables (posttest 2) Box diagram

In phase 3: Definition of objective function, Fig. 13 details similar results in the pretest, with a median of 1 for both groups.

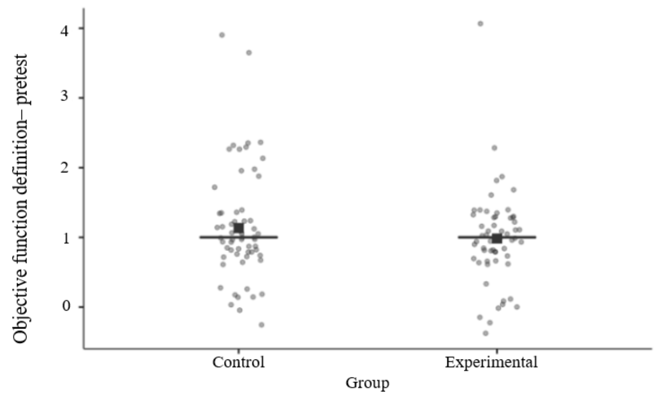

Fig. 13. Dimension 3 - Definition of objective function (pretest)Box diagram

In the posttest 1 and in the posttest 2, the dimension: Definition of objective function, obtained medians of 4 for both groups (Fig. 14 and 15), however in the posttest 2 a difference in the proportion of frequencies is seen, leaving the experimental group in a higher position.

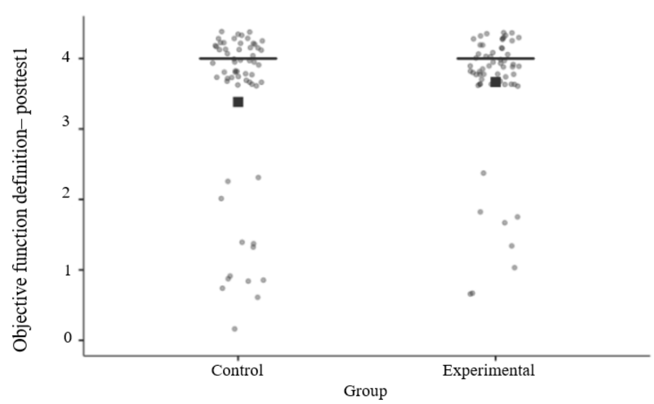

Fig. 14. Dimension 3 - Definition of objective function (posttest 1) Box Diagram

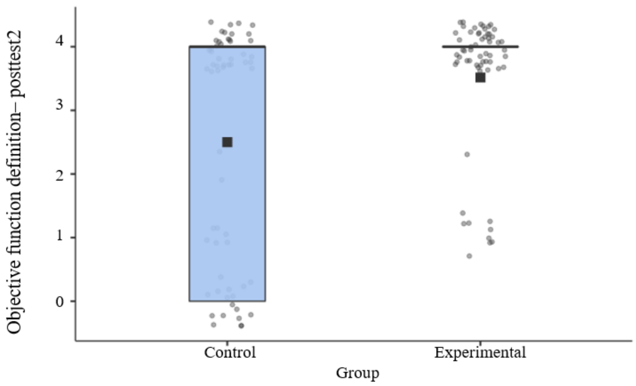

Fig. 15. Dimension 3 - Definition of objective function (posttest 2) Box diagram

In phase 4: Identification and definition of constraints, Fig. 16 details similar results in the pretest, with a median of 1 for both groups.

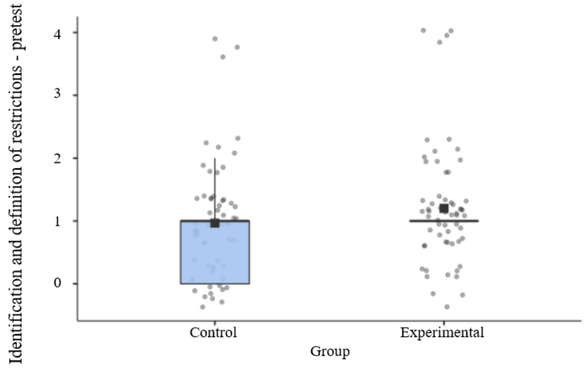

Fig. 16. Dimension 4 - Identification and definition of constraints (pretest) Box diagram

In posttest 1, the dimension: Definition Identification and definition of constraints obtained medians of 4 for both groups (Fig. 17), while in posttest 2 (Fig. 18) the medians were 2 (control group) and 4 (experimental group) highlighting the stimulus group.

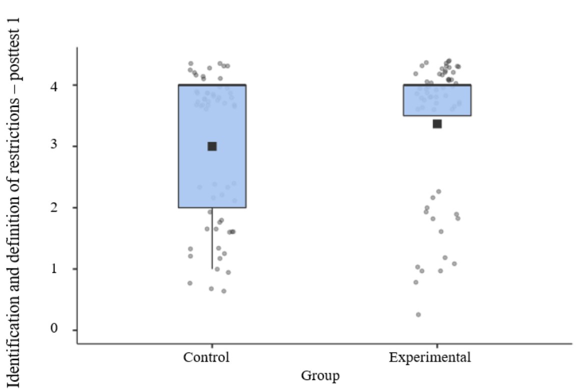

Fig. 17. Dimension 4 - Identification and definition of constraints (posttest 1) Box diagram

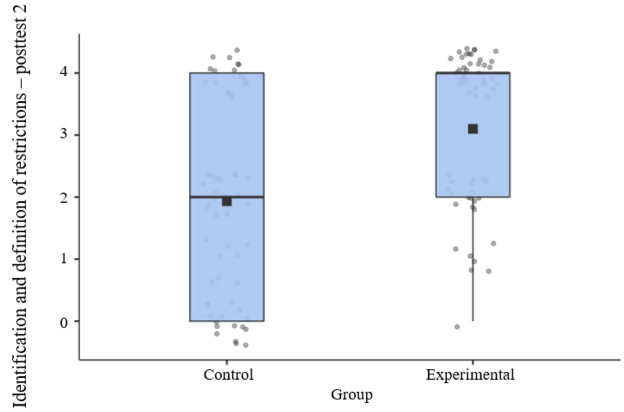

Fig. 18. Dimension 4 - Identification and definition of constraints (posttest 2) Box diagram

Finally, in phase 5: Obtaining the LP model, Fig. 19 shows similar results in the pretest, with a median of 0 for both groups.

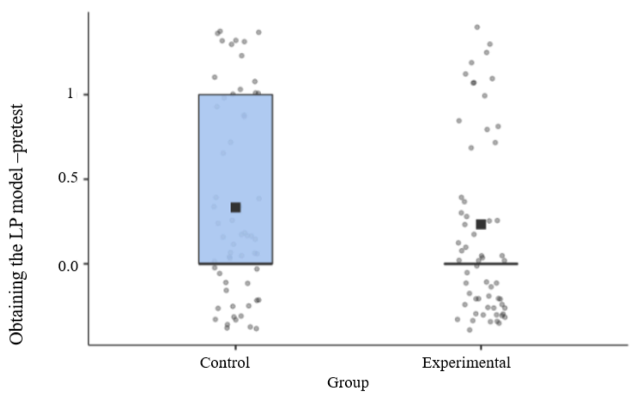

Fig. 19. Dimension 5 - Obtaining the LP model (pretest) Box diagram

In posttest 1, the dimension: Obtaining the LP model obtained medians of 2 (control group) and 4 (experimental group) (Fig. 20), while in posttest 2 (Fig. 21) the medians were 1 (control group) and 4 (experimental group) highlighting the stimulus group.

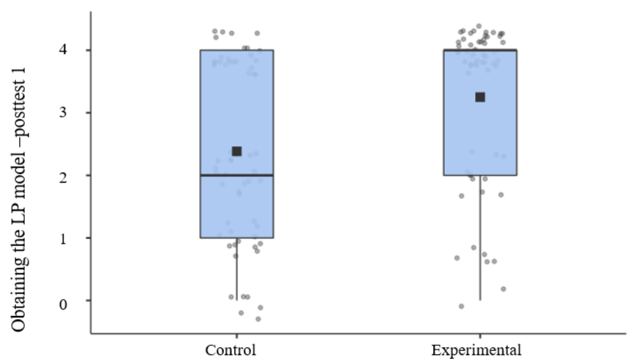

Fig. 20. Dimension 5 - Obtaining the PL model (posttest 2) Box diagram

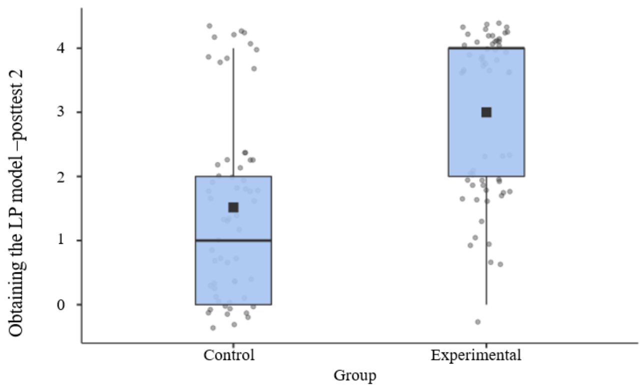

Fig. 21. Dimension 5 - Obtaining the LP model (posttest 2) Box diagram

Stage 1 and 3 learning behavior similarly in both groups. Descriptive differences are found in stages 4 and 5, being the finals of the process where there is greater difficulty and precision in earlier stages. Finally, in the hypothesis testing, significance obtained a p value < α=0.01, both for the independent variable and in its dimensions (Table I) [4].

TABLE I. HYPOTHESIS TESTING

Variable /Dimensions	**Sig.**
Dimension 1: Building LP models	.000
Dimension 2: Identification of variables	.001
Dimension 3: Defining variables	< .001
Dimension 4: Definition of the objective function	< .001
Dimension 5: Identification and definition of constraints	< .001
Variable: Obtaining the LP model	< .001

The results showed that the application of neuroeducation strategies significantly improved the level of construction of LP models. Agrees with Diaz et al. [10], related to motivational performance, with Al-Balushi y Al-Balushi [11] that achieved superior performance in the experimental group. In addition, with Tacca et al. [14], with a positive correlation of 0.72 of Spearman and with Valdivieso et al. [9] with 0.038 and Ballesta-Claver et al. [12].

Similarly, Vigo [13] was agreed upon for the design of the neurodidactic model with an acceptance and improvement of learning by 64%, and finally similarities were found with the study by Plaza et al. [15] for the application of the principles of neurodidactics in mathematics and the fight against anxiety and demotivation in its study. This research included learning in a pleasant and meaningful way, managing to stimulate the taste for mathematics in LP, with active participation, ingenuity and innovation, and above all solving real problems, as mentioned by Polya [7].

IV. Conclusions And Recommendations

The study concluded with the identification of the significant effect of neuroeducation in the construction of LP models with p=0.000 less than α= 0.01 in the Mann Whitney U test. At the level of dimensions related to the phases of the method, in identification of variables, (p <0.001), in definition of variables (p = 0.002), in definition of objective function (p <0.001), in identification and definition of constraints (p <0.001) and in obtaining the LP model (p <0.001), with a difference greater than 15% of the experimental group over the control group, related to the level of construction of the LP model.

It requires training and knowledge of how the brain of students learns, managing to understand how higher cognition devices are activated (memorize, attend, motivate, and pay attention), which allows integration into engineering training subjects in search of the long-awaited meaningful learning.

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