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Self-Assessment and Task Selection Skills Training, Cognitive Approach to Developing Self-Regulated Learning: Replication Study Kostons et al. (2012)

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Abstract

It is necessary that students learn to self-regulate their learning and develop cognitive and metacognitive processes to accurately measure their academic performance and select the next activity, in such a way that it complements or feeds back the knowledge or skills learned and provides an achievable challenge. To determine whether training with self-assessment models and task selection models leads to greater accuracy in self-assessment and task selection, replication of experiment one of Kostons et al. (2012) was conducted. 160 students from the General Unified Baccalaureate participated. The results suggest that training in self-assessment and task selection skills improve the accuracy of these skills (hypothesis 1). It was partially proven that one skill does not transfer or improve the performance of the other (hypothesis 2). It was also demonstrated that these skills are not inherent to the individual and require training..

Keywords: *Self-regulated learning, self-assessment, task selection, education, skill modeling.*

1. Introduction

One of the interests of education is that students are the protagonists of their training and can self-regulate their learning (Cázares et al., 2020). In order for the student to achieve better learning outcomes, cognitive and metacognitive processes must be developed that drive self-regulated learning (Arias et al., 2019). Several studies (Kenny & Fonseca, 2020; Kostons et al., 2010, 2012; Zimmerman, 2002) demonstrate that the effectiveness of self-regulated learning is achieved when the student self-evaluates, accurately measuring his performance in the activities performed, to properly select the next learning task when he has control over them.

According to Velázquez (2020), the training students receive in the development of cognitive and metacognitive strategies is scarce. Inaccuracies in self-assessment and task selection are due to poor training in these skills and result in ineffective self-regulated learning (Cázares et al., 2020; Kostons et al., 2010). According to Combina (2020), analyzing and understanding the role of training in cognitive and metacognitive processes allows the design of high-impact educational

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June 2023
Volume: 8, No: 4, pp. 2584 - 2605
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strategies. The present study was carried out with students of the Unified General Baccalaureate of the Carlos Larco Hidalgo Educational Unit, of the Rumiñahui canton, of the Province of Pichincha. It aimed to determine whether training with self-assessment models and task selection models leads to greater accuracy in self-assessment and task selection. Two hypotheses are formulated: Training in self-assessment skills and task selection improve the accuracy of these skills (hypothesis 1). Training one skill, self-assessment, or task selection does not transfer to or improve the performance of the other (hypothesis 2).

Self-regulated learning

Self-regulated learning takes hold in the 80s. It deals with the autonomy and commitment of the student with academic activities and the impact on the quality of learning when the student establishes objectives, learning models and increases the perception of themselves and the task (self-evaluation) (Álvarez Valdivia, 2009). For Zimmerman & Moylan (2009) it is about the strategic control of thoughts, actions and motivations to achieve personal learning outcomes in an adaptive way. Kaplan (2008) explains that it is the way in which the student understands the learning task, his commitment and desire to perform it, in addition to compromising his motivation and will.

Therefore, self-regulated learning is the student's ability to intentionally manage the cognitive, metacognitive and emotional processes involved in their learning, and transforms their mental abilities into learning skills through self-awareness and self-motivation (Aurah, 2013; McCombs & Marzano, 1990; Zimmerman, 1990). One of the best-known models of self-regulated learning, according to several authors (Harding et al., 2018; Baker & Alonso Tapia, 2014; Sáiz-Manzanares & Pérez Pérez, 2016; Trias, 2017; Zambrano et al., 2018) is the cyclical phase model of Zimmerman & Moylan (2009), where the three phases of self-regulated learning are established (Figure 1): planning, execution, and self-reflection.

The article refers to the phase of self-reflection. Self-assessment and the selection of learning tasks when the student has control of the tasks are skills that allow judging the performance of the activities and the reaction to select the most appropriate task.

Figure 1

Self-Regulated Learning Phase (Zimmerman & Moylan, 2009).

June 2023
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Self-Assessment and Task Selection Skills

The correct execution of an educational activity depends on the relationship of the mental resources required by a task and the ability of the student to provide the resources required (Cain, 2007; Hancock & Chignell, 1987). To measure this cognitive load is divided into three dimensions: (1) the mental load to relate the characteristics of the task (format, time complexity, equipment and others) and the characteristics of the student (age, experience, skills and others), (2) the mental effort to measure the mental or intellectual requirements and levels of processing of the information required to execute the task, (3) performance to measure the achievements achieved when executing a task in terms of number of hits, errors, execution time and others (Clavijo Lozano et al., 2011; Kirschner, 2002; Sweller, 2010; Sweller et al., 1998).

According to Azevedo & Cromley (2004), Bol et al. (2016), Kostons & Paas (2012), Kostons et al. (2010b) the training in self-regulated learning skills serves so that the student has a greater precision in the monitoring (self-evaluation) and control (selection of tasks) of educational activities and correct execution. Corbalan et al. (2008) explains that adaptive instruction systems achieve effective learning, when the student selects the next learning task based on the self-evaluation of their performance and the mental effort invested in solving the previous task.

When the student self-evaluates their performance, they make a quantitative or qualitative assessment of the activities, actions or products during a period of learning, activity or task to

June 2023
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measure the development of their skills or results (Irigoyen et al., 2011). The selection of tasks occurs when there are educational environments in which the student has control of the activities or tasks that he is going to perform and is required to choose the most appropriate activity or task to meet his educational needs (Kostons & Paas, 2012).

Modeling and Skills Training

Modeling, known as observational learning or vicarious learning, highlights the relevance of imitation in learning processes and skills training (UNED, 2018). Cormier & Cormier (2000) explains that modeling is a process where the behavior or procedures of one or more individuals influences the attitudes, practices, abilities, or behaviors of other individuals who witnessed the demonstration of the model.

Méndez & Olivares (2014) synthesize Bandura's modeling theory in (a) human behavior is generally learned by observing a model, (b) behavior that is acquired or modified through experiences can be acquired or modified by the behavior of others and their consequences, (c) individuals acquire symbolic representations of the model. Therefore, imitation aims to: (1) acquire new response patterns, (2) strengthen or weaken responses and, (3) facilitate the execution of existing responses in the individual.

Attention, retention, reproduction and motivation are the basic processes of modeling and allow the observed to assume as their own the objectives proposed through modeling techniques (Bandura & Jeffrey, 1973). There are a large number of modeling techniques, four techniques of the classification made by Labrador et al. (2001) are described:

- According to the behavior of the observer: (a) passive modeling where the individual only observes the model and does not reproduce it during training, (b) active modeling when the individual more than seeing the model replicates it in the same session.
- According to the presentation of the model: (a) symbolic modeling: when the model is presented through audio, videos or images, (b) live modeling when the model is presented in person.
- According to the adequacy of the behavior of the model: (a) positive modeling when the correct behavior or procedure is shown, (b) negative modeling when the unwanted behaviors or processes are shown. (c) mixed modeling when positive and negative modeling is interspersed.
- According to the number of models: (a) simple modeling when only one model is presented, (b) multiple modeling when several different examples of the model are presented.

June 2023
Volume: 8, No: 4, pp. 2584 - 2605
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The experiment carried out in the present study uses examples of models in which the observer is passive, the presentation is symbolic, with a mixed behavior and applies multiple modeling.

Self-Assessment Skills Modeling and Task Selection

Kostons et al. (2012) investigated modeling self-assessment skills and task selection, how these skills can be improved and self-regulated learning fostered. They worked with 80 Dutch students (male = 36, female = 44; age M = 15.23, SD = 0.53) from the highest level of secondary education in the Netherlands. The study confirmed that training in self-assessment skills and task selection, based on training modeling examples, improves the accuracy of these skills (hypothesis 1). The authors believe that these skills play an important role in the effectiveness of self-regulated learning. It was also found that training one skill, self-assessment or task selection, does not transfer or improve the performance of the other (hypothesis 2), They found no interaction effects between the two skills that suggest that training one of them leads to the accuracy of the other.

Kostons et al. (2012) used two-factor ANOVA to test hypotheses, self-assessment modeling and task selection modeling as factors and significance level set at 0.05; the result was the rejection of H0. It is evident that the examples of modeling of inheritance problems allowed students to solve the exercises in the subsequent test. The two-factor ANOVA with examples of self-assessment models and examples of task selection models as independent variables and the gain of the pre- and post-test as a dependent variable showed no significant differences between the conditions.

Two-factor ANOVA analysis with examples of self-assessment models and examples of task selection models as independent variables and accuracy of self-assessment as dependent variable demonstrated that students who received the self-assessment models were more accurate than those who did not receive the model. The two-factor analysis with examples of self-assessment models and examples of task selection models as independent variables and the accuracy of task selection as a dependent variable demonstrated that students who received the task selection models were more accurate than those who did not receive the model.

This study

Inaccuracies in self-evaluation and task selection is a constant phenomenon in the study group, they are students who have received no or little training in these skills, which is why the replication of the number one experiment of the research of Kostons et al. (2012) was carried out to contrast the information obtained and specify the results when dealing with similar problems. We aimed to demonstrate that training based on examples of assessment skills and task selection allows students to have greater accuracy in self-assessment and task selection when they have control over the activities they practice. The procedure carried out by Kostons et al. (2012) brings together the theoretical and methodological elements on the problem, which allowed to have

June 2023
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solid results with which it was possible to analyze the effects of training based on examples of self-assessment skills and task selection in the resolution of inheritance problems in the subject of Biology and establish whether the training of a skill, Self-assessment or task selection, transfers and improves the performance of the other.

Method

Participants

160 students (73 men, 87 women) of Unified General Baccalaureate of a Carlos Larco Hidalgo Educational Unit of the Rumiñahui canton of the Pichincha province of Ecuador participated. Due to the health measures imposed by the COVID-19 pandemic, participants received classes through videoconferences and educational platforms. A 2 X 2 factorial design was used, the first factor being examples of self-assessment modeling (Si vs. No) and the second factor is examples of task selection modeling (Yes vs. No). Each participant was randomly assigned to one of the following conditions: (1) examples of self-assessment models and task selection (n = 40), (2) only examples of self-assessment models (n = 4), (3) only examples of task selection (n = 40), or (4) no examples of self-assessment models or task selection (n = 40). Until the time of the experiment, the students did not formally receive knowledge about Mendel's Laws, the subject of the study materials.

Instruments

Preliminary and Post-Test

Each test contained five inheritance problems for applying Mendel's Laws, each problem corresponding to one of the five levels of complexity (see complexity levels Table 1; see example of inheritance problem Appendix 1; see sample questions from the test Appendix 2). The "Cloze embedded responses" tool of the Moodle platform was used to design each item. Using Moodle's Active Quiz tool, problems were presented randomly according to their complexity. The problems of the pre- and post-test were similar in their structure and difficulty, different in their wording, that is, they are not identical.

Each problem was solved in five steps: (1) Determine the genotypes (two uppercase and/or lowercase letters representing dominant or recessive, homozygous or heterozygous alleles) of the parents (P#) or offspring (F#) described in the problem statement; (2) design the hereditary tree with the genotypes; (3) set how many Punnett tables you will use; (4) Complete the Punnett tables; (5) determine the solution or solutions. Each correctly performed step equals one (1) point, the maximum score of each problem is five points and the maximum total of the test is 25 points.**Board 1**

Task Selection Database

June 2023
Volume: 8, No: 4, pp. 2584 - 2605
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COMPLEXITY	SUPPORT	LEARNING EXERCISES				
Level 1 - 2 generations - 1 unknown - 1 solution - Deductive	High	Ex. - 01	Ex. - 02	Ex. - 03	Ex. - 04	Ex. - 05
	Low	Ex. - 06	Ex. - 07	Ex. - 08	Ex: - 09	Ex. - 10
	None	Ex. - 11	Ex. - 12	Ex. - 13	Ex. - 14	Ex. - 15
Level 2 - 2 generations - 1 unknown - Multiple solutions - Deductive	High	Ex. - 16	Ex. - 17	Ex. - 18	Ex. - 19	Ex. - 20
	Low	Ex. - 21	Ex. - 22	Ex. - 23	Ex. - 24	Ex. - 25
	None	Ex. - 26	Ex. - 27	Ex. - 28	Ex. - 29	Ex. - 30
Level 3 - 2 generations - 1 unknown - Multiple solutions - Inductive	High	Ex. - 31	Ex. - 32	Ex. - 33	Ex. - 34	Ex. - 35
	Low	Ex. - 36	Ex. - 37	Ex. - 38	Ex. - 39	Ex. - 40
	None	Ex. - 41	Ex. - 42	Ex. - 43	Ex. - 44	Ex. - 45
Level 4 - 3 generations - 1 unknown - Multiple solutions - Deductive, Inductive	High	Ex. - 46	Ex. - 47	Ex. - 48	Ex. - 49	Ex. - 50
	Low	Ex. - 51	Ex. - 52	Ex. - 53	Ex. - 54	Ex. - 55
	None	Ex. - 56	Ex. - 57	Ex. - 58	Ex. - 59	Ex. - 60
Level 5 - 3 generations - 2 unknown - Multiple solutions - Deductive, Inductive	High	Ex. - 61	Ex. - 62	Ex. - 63	Ex. - 64	Ex. - 65
	Low	Ex. - 66	Ex. - 67	Ex. - 68	Ex. - 68	Ex. - 70
	None	Ex. - 71	Ex. - 72	Ex. - 73	Ex. - 74	Ex. - 75

Note: The database contains 5 exercises for each support level, 3 support levels for each complexity level, and 5 complexity levels. Each exercise is numbered, they were labeled with the prefix "Ej" of exercise, followed by the consecutive number (Eg - ##).

Mental Effort

June 2023
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For the mental effort test, the nine-point scale used by Pass (1992) was used, ranging from (1) "very, very little effort" to (9) "much, very much effort". The test was applied after each problem of the pre- and post-test. The measurement of mental effort was used for the student to properly select the next task to solve.

Self-evaluation

For the self-assessment, a six-point rating scale was used, ranging from (0) Considers that you did not solve any step to (5) considers that you correctly solved the five steps (Kostons et al., 2012). The students self-rated their performance on each problem after measuring their mental effort. The score achieved in the self-assessment was used for the student to properly select the next task to solve.

Task Selection

For the selection of tasks, the student chose the following exercise from a database with 75 inheritance problems (Table 1), distributed in five levels of complexity. Each complexity level contained five exercises with "high support" (all answers to select), five exercises with "little support" (with some answers to select and others to complete), and five "unsupported" exercises (all answers to complete). The exercises of each level were similar in their structure and difficulty, different in their wording and according to the level of support. Each problem within a level of complexity can be solved using the same procedure. It is important to note that the student should not solve the selected problem, only what was his option is indicated.

For the student to make a correct selection of the next task, a relationship table between self-assessment and mental effort was used (Table 1), where the student, manually, must identify how many rows should advance or retreat to choose the next task. Procedure similar to the task assignment system algorithm used by Camp et al. (2001), Corbalan et al. (2008) and Salden et al. (2004, 2006).

Board 1

Relationship Self-Evaluation and Mental Effort

Self-evaluation			
4 – 5	+2	+1	0
2 – 3	+1	0	-1
0 – 1	0	-1	-2
	1, 2, 3	4, 5, 6	7, 8, 9
	Mental effort		

Volume: 8, No: 4, pp. 2584 - 2605
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Note: Determines the number of rows you must advance or rewind to select the next learning task.

Modeling Example

Each group of participants was explained, through four videos, how to solve inheritance exercises using Mendel's Laws. The videos were recorded by the authors. Each video contained an example of modeling, and two male and two female models were used to prevent the gender of the model from influencing learning and affecting self-efficacy (Schunk, 1989). According to the condition assigned to the group, the videos showed: (1) the model solving an inheritance problem, self-evaluates its performance, measures its mental effort and selects a new task using the relationship table self-evaluation mental effort for the condition of examples of self-evaluation models and task selection; (2) the model solving an inheritance problem, measures its mental effort and selects a new task for the condition of task selection examples; (3) the model solving an inheritance problem, self-evaluates performance and selects a new task without using the table for the condition of examples of self-assessment models, (4) the model solving an inheritance problem and selected a new task without using the table for the condition without examples of self-assessment models or task selection. The content of the videos was as follows:

1. Troubleshooting (all conditions). The model made a verbal explanation supported by graphic material of the resolution of an inheritance problem, the steps that were performed and why they were performed. Two models worked on problems of complexity 1 and two on problems of complexity 2 (see complexity levels Table 1). To prevent the self-assessment and the mental stress test from having the same scores, the first model solved the problem without errors, the other models made one or more errors (Table 3).

Board 2

Features of the Modeling Example

Example	Model	Number of errors	Complexity Level
1	Female 1	0	2
2	Male 1	1	1
3	Female 2	3	2
4	Male 2	2	1

Note: The table indicates the gender of the model, the number of errors you must make in explaining the problem, and the level of complexity of the problem you are solving.

2. Self-assessment for the conditions of examples of self-assessment models and task selection and examples of self-assessment models. The models explained verbally and supported with

Remittances Review
June 2023
Volume: 8, No: 4, pp. 2584 - 2605
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graphic material how to self-evaluate performance, assigning a point to each correctly performed step of the problem and recording it on the 6-point scale. The self-assessment corresponds to the number of errors you make in explaining the problem, explaining what was the mistake you made.

3. Mental stress test for the conditions of examples of self-assessment and task selection models and examples of task selection. The models explained verbally and supported with graphic material how to measure mental effort, using the 9-point scale of Pass (1992). The mental exertion score varies in each video.

4. Task selection (all conditions). For the condition of examples of self-assessment models and task selection, the model explained how to use the relationship table between self-assessment and mental effort (Table 2), to identify how many rows should be advanced or backward in the exercise database (Table 1). For example, a self-assessment of four and a mental effort of three indicates that you should select any exercise two rows below the row where the current exercise is located. If the relationship table gives a positive number, it indicates that the student is ready to move forward in the level of complexity or reduce the level of support; If it is a negative number, a problem with less complexity or with more support should be selected and if it gives zero (0) it advises that another exercise of the same row be carried out to correct Some mistakes made. The selection of tasks for the condition of examples of self-assessment models and task selection was obtained from the self-assessment and mental effort indicated in the video. For the other conditions only the next task is selected without giving explanations.

Participants of the condition without examples of self-assessment models or task selection, after observing the resolution of the problem, were asked to indicate, if the model made any errors during the explanation and how it should correct it. In this way, the group aims to promote the acquisition of problem-solving skills through identifying and correcting errors (Große & Renkl, 2007).

Procedure

The experiment was conducted using the Moodle Virtual Learning Environment. Participants were randomly assigned to each of the four conditions, trying to maintain proportionality in number and gender. The participants were registered in the virtual classroom according to the assigned condition, they were given username and password of the Moodle platform and their access was verified. Through WhatsApp messages, the invitation to the videoconference by Zoom was distributed to each group.

At the beginning of the meeting (the average meeting time was 90 minutes) they received an explanation of the experiment, the self-assessment, mental stress test and the levels of complexity and support from the training database. After the introduction to the experiment they performed the previous test, the Active Quiz tool of Moodle was used to control that all students execute the exercises at the same time and that they are the same for all participants. After each inheritance problem they had to self-evaluate, measure their mental effort and select (only select, not solve) a new learning task. They had four minutes to solve exercise and one minute to evaluate their performance and select the next learning task. The time allotted for conventional problem solving was validated by the study by Kostons et al. (Kostons et al., 2010). Students did not receive the score obtained, nor were comments made on self-assessment, measurement of mental effort or task selection. Participants could not solve the selected task.

After the preliminary test, the students were projected the videos with the explanation of the model according to their condition. Finally, the students took the subsequent test with the same procedure as the previous test. The analysis of the results of the study was carried out with the entire population, prior to its review. The research direction of the Universidad Del Pacífico de Guayaquil - Ecuador, carried out the monitoring and approval of the research.

Results

To verify if there are statistically significant differences between the four conditions, the data were analyzed with ANOVA. The conditions of examples of self-assessment models and task selection, examples of self-assessment models, examples of task selection and no examples of self-assessment models or task selection were used as a factor and the significance level was .05. The effect size is interpreted according to the scale proposed by Cohen (1988): small effect .01 > ηp2 < .06, median effect .06 > ηp2 < .14, and large effect ηp2 > .14. The experiment was conducted online and due to connection problems 11 students (three in examples of self-assessment models and task selection, three in examples of self-assessment models, three in examples of task selection and two in the condition without examples of self-assessment models or task selection) did not finish the posttest. Precision analysis is not performed in the self-assessment and task selection of the pretest, because the data collected is imprecise, the students did not know about the subject of study and have not developed self-assessment and task selection skills.

The average score obtained by students in the pretest is .59 (SD = .89) and the average posttest is 10.78 (SD = 3.68). To determine if there was any difference between the conditions as an independent variable and the pretest and posts as dependent variables, ANOVA was performed. This analysis found no significant differences in the pretest (F(3, 156) = 1.36, p = .26, ηp2 = .03, MCE = .79).

In the posttest a difference was recorded (F(3, 145) = 3.24, p = .02, ηp2 = .63, MCE = 12.96), the condition of examples of self-assessment models and task selection (M = 12.14, SD = 4.10) registers a significant difference (p = .01) with the condition without examples of self-assessment

Volume: 8, No: 4, pp. 2584 - 2605
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models or task selection (M = 9.55, SD = 3.55). These scores indicate that students managed to learn in solving inheritance problems, without exceeding the average of 12.5. With this information, the performance achieved by the participants in solving inheritance problems (posttest – pretest) was calculated. ANOVA of conditions as an independent variable and performance as a dependent variable, revealed no significant differences between the conditions ($F(3, 145) = 2.33$, $p = .08$, $\eta p2 = .05$, MCE = 13.11).

Board 3

Means and Standard Deviation by Category and Variable

ITEM	Examples of self-assessment models and task selection	Examples of self-assessment models	Examples of task selection	No examples of self-assessment models or task selection
Pretest	.80 (1.20)	.50 (.64)	.63 (.77)	.43 (.84)
Poles	12.14 (4.10)	10.81 (3.07)	10.65 (3.62)	9.55 (3.55)
Performance achieved	11.30 (4.01)	10.30 (3.08)	10.00 (3,72)	9.11 (3.62)
Post-test self-assessment effectiveness	1.03 (.55)	.97 (.44)	1.70 (.66)	1.53 (.65)
Effectiveness of post-test task selection	.49 (.51)	.89 (.52)	1.30 (.74)	3.03 (2.12)

Note: Standard deviation values are in parentheses.

To determine the accuracy in the self-assessment, the absolute difference of the score achieved by the students in the posttest and self-assessment was calculated. For example: the grade of the solved exercise is two and in the self-evaluation the student selected three, the precision achieved ($ABS(2 - 3) = 1$) in the self-evaluation is one. Values close to zero mean high accuracy, while values far from zero mean low precision. To maintain objectivity in the calculation of accuracy in the self-assessment, records with zero score in the exercise and self-assessment were not included, it is very easy for the student who did not answer the exercise to place a self-assessment of zero, which would result in high accuracy wrong.

The accuracy in the self-assessment was taken as the dependent variable and the conditions as independent variables of the ANOVA, finding a strongly significant difference ($F(3, 145) = 14.41$, p = .00, ηp2 = .23, MCE = .34). The statistical difference found would support hypothesis 1 by verifying that conditions that were trained in self-assessment skills (examples of self-assessment models and task selection and examples of self-assessment models) improved the accuracy of this skill. The condition of examples of self-assessment models and task selection shows no differences (p = .98) with the condition of examples of self-assessment models. Strongly significant differences are recorded: the condition of examples of self-assessment models and task selection with the condition of examples of task selection (p = .00) and with the condition without examples of self-assessment models or task selection (p = .00), the condition of examples of self-assessment models with the condition of examples of task selection (p = .00) and with the condition without examples of self-assessment or selection models of tasks (p = .00). The condition of examples of task selection and the condition without examples of self-assessment models or selection of tasks have no significant differences between them (p = .56). These results would support hypothesis 2, showing that the condition that received training in task selection (examples of task selection) could not transfer that learning for self-assessment.

To calculate the accuracy in the selection of tasks in the posttest, the row in which the student is recommended to select the next exercise was determined, using the relationship table between self-evaluation and mental effort (Table 2). Example: Suppose that the student solved exercise 17, in the self-evaluation he marked four and in mental effort two; Table 2 indicates at its intersection +2, the student should go two rows down the row of exercise 17 and select any exercise between 26 and 30. Once the number of rows that it is recommended to move to select the next exercise is determined, the absolute difference between the number of rows between the solved exercise and the next selected exercise with the recommended number of rows is calculated. Example: taking the previous example and assuming that the student selected as the next exercise the number 42, between the row of exercise 17 and the row of exercise 42 there are five rows, except the two suggested rows, a precision is obtained in the selection of tasks of three. Values close to zero mean high accuracy, while values far from zero mean low precision.

To analyze the selection of tasks, ANOVA was performed with the conditions as independent variables and the precision in the selection of tasks as a dependent variable. The analysis found a strongly significant difference (F(3, 145) = 31.07, p = .00, ηp2 = .39, MCE = 1.51), which would indicate that conditions that received training in task selection skills (examples of self-assessment and task selection models and examples of task selection) improved the accuracy of this skill confirming hypothesis 1. The condition of examples of self-assessment models and task selection shows no difference (p = .98) with the condition of examples of self-assessment models, as does the condition of examples of self-assessment models with the condition of examples of task selection (p = .49). Strongly significant differences are recorded from the condition of examples of self-assessment models and task selection with the condition without examples of self-

June 2023
Volume: 8, No: 4, pp. 2584 - 2605
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assessment models or task selection (p = .00), the condition of examples of self-assessment models with the condition without examples of self-assessment models or task selection (p = .00) and the condition of examples of task selection with the condition without examples of self-assessment models or Task selection (p = .00). There is a significant difference between the condition of examples of self-assessment and task selection models and the condition of examples of task selection (p = .03). These results suggest that the condition of examples of self-assessment models (M = .89), which did not receive training on task selection, achieved a precision in the selection of tasks close to the conditions that received training in that skill, examples of self-assessment models and task selection (M = .49) and examples of task selection (M = 1.30). Apparently, the ability of self-evaluation helped to achieve a better precision in the selection of tasks, partially contradicting hypothesis 2.

Discussion

To determine whether training with self-assessment models and task selection models leads to greater accuracy in self-assessment and task selection was the aim of the study. In relation to hypothesis 1, the experiment found that teaching students self-assessment and task selection skills, through model examples, does improve the accuracy of these skills. The three experimental conditions that received training in one skill, or both, self-assessment or task selection, showed significant differences compared to the control group that did not receive any training in these skills. That is, these skills need to be formed in students to achieve high accuracy in self-assessment and task selection. This result is consistent with that described in several studies (Kostons et al., 2010, 2012; Raaijmakers et al., 2018; van Gog vangog et al., 2010) that highlight the effectiveness of video modeling examples in training self-assessment skills and task selection. In all the studies, the participants who received the training significantly increased the accuracy when self-evaluating and selecting the next task when they have control of them.

Sharma et al. (2016) and McDonald & Boud (2010) conducted studies on self-assessment training (not task selection), observed that students' academic performance improved significantly after having trained students in self-assessment skills and their implementation. Students achieved a significantly positive correlation between the qualification of the teaching staff with that of their self-evaluation. For their part, Baars et al. (2014) suggest that delivering written self-assessment standards is more effective than training with examples.

The results found by Baars et al. (2014) could be justified by the fact that the student has permanent access to written self-assessment instructions and can review them several times, which does not happen with model examples, because they only see it at a moment. Corbalan et al. (2008) reviewed the effects of adaptation and shared control of task selection on learning effectiveness and engagement in work, and suggests that adaptation led to more efficient learning and shared control over task selection led to greater task engagement.

This study analyzed the implications of training versus no skills training, it is necessary to expand the research to confront the training with examples of models with other forms of instruction such as norms, indications, practices or others. In addition, taking into account the importance of the student self-regulating, we cannot forget the control that the teacher must perform over the tasks performed by the student in order to provide support that covers the needs of the student.

On hypothesis 2 that sought to demonstrate that the training of one skill, self-evaluation or task selection, do not transfer, nor improve the performance of the other, the results suggest that teaching self-evaluation allowed inferring the task selection procedure and improving accuracy in the two skills. What did not happen when teaching to select tasks, that is, this skill did not lead to greater accuracy in self-assessment. The results found differ from the studies of Kostons et al. (2010, 2012), in which they suggest that skills are not transferred. These results can be explained because according to Andrade (2019) and Raaijmakers et al. (2018, 2019) self-assessment allows the individual to review their own processes and products to adjust and deepen learning, improving performance. The authors suggest that self-assessment, as a pillar of self-regulated learning, leads to increasingly satisfying achievements. In addition, when the student evaluates himself, he is criticizing and analyzing his own work, which produces an increase in interest and motivation for the activities he performs (Sharma et al., 2016). For these reasons, it is possible that the student, when self-evaluating, takes with greater responsibility the selection of the next task to be performed.

The study did not test whether self-assessment and task selection lead to better performance in learning a specific subject. The scope of these skills should be deepened and their effect on self-regulated learning of a subject and whether these skills are transferred to different topics should be analyzed. For example, after training self-assessment and task selection using Biology exercises, determine whether these skills improved performance in learning that subject and whether this process is transferred to Mathematics or another subject.

The results presented allow us to recommend that within the educational priorities, cognitive and metacognitive skills and processes should be developed so that students become autonomous learners, who properly manage their learning and clearly identify their educational priorities. The teacher must encourage students to organize and direct their own learning processes and activities, becoming a counselor and mediator of learning. It is also important that the training processes avoid cognitive overload, turn the difficulties of the tasks into challenges that the student can escalate through the support he finds in the selected learning task.

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Appendix

Appendix 1

Example of a task at complexity level 2

Utterance.

In the vinegar fly, the red-eyed character is dominant over white-eyed. Two heterozygous red-eyed flies interbreed and produce offspring. What phenotypic and genotypic ratio is expected in your offspring?

Use:

A = dominant, A = recessive

P1 = parent1, P2 = parent2 ... Pn = N parent

F1 = first offspring, F2 = second offspring ... Fn = N offspring

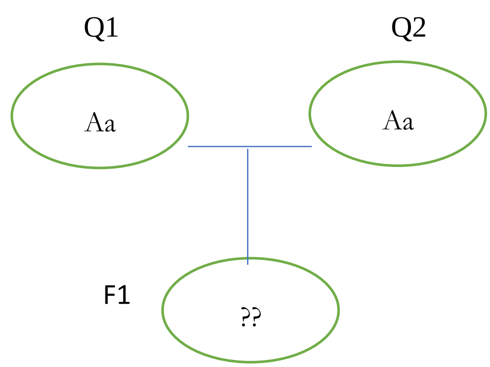
Step 1: Determine genotypes

Genotype Father

Q1 ➔ Aa (heterozygous dominant)

Q2 ➔ Aa (heterozygous dominant)

Step 2: Design of the hereditary tree with the genotypes.



Step 3: Determine how many Punnett frames to use.

Number of Punnett frames: 1

Step 4: Prepare the Punnett chart(s).

Use the tables in order of descent: F1, F2 ... and in order of genotype: AA - Aa - aa

Table 1		**Q2**	
		To	to
Q1	To	AA	Aa
	to	Aa	Aa

Step 5: Final answer (place your answer in hierarchy order: AA - Aa - aa)

The possible genotypes of F1 are: (place your answers in order of hierarchy: AA - Aa - aa)

AA ➔ 25%

Aa ➔ 50%

Aa ➔ 25%

The predominant phenotype in F1 is: (place your responses in order of hierarchy: Dominant - Recessive)

Red ➔ 75%

White ➔ 25%

Appendix 2

Post-test

Question 1, level 2

In humans and chimpanzees there are individuals who can perceive low concentrations of phenylthiocarbamide (PTC), called tasters (A), and individuals who cannot perceive even at high concentrations, called non-tasters (a), assuming that the taster character is dominant and non-tasters in its recessive form. Two individuals liking heterozygous trait produce offspring (F1). What are the possible genotypes and phenotypes of this offspring?

Question 2, level 4

Galactosemia is an autonomic recessive character. A normal heterozygous marriage (P1 and P2) has a child (F1) whose genotype is unknown. The boy procreates a baby (F2) affected by galactosemia, it is known that the mother (P3) was affected by galactosemia. What is the genotype of the child from the first marriage?

Question 3, Level 1

In a guinea pig the coat color is determined by a gene, which is expressed as black in its dominant form (A) and white in its recessive form (a). Two guinea pigs, which are black and heterozygous by that trait, produce offspring (F1). What is the predominant phenotype of this offspring?

Question 4, level 5

Cystic fibrosis (CF) is caused by a gene that is expressed in its recessive form, but not in its dominant form. Two parents have offspring. One parent has CF, the other parent's genotype is unknown. The offspring (F1) they produced has no CF and is heterozygous for this trait. This offspring, along with their non-CF partner who is heterozygous for the trait, also produces offspring (F2), whose genotype is unknown. What are the possible genotypes of the unknown father and offspring?

Question 5, level 3

In mice there is a dominant allele that determines the normal shape of the ear (A) and a recessive allele that determines crooked ears (a). A mouse (F1) has the same homozygous dominant allele as one of its parents. What is the genotype and phenotype of the other parent?

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