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Category learning in schoolchildren. Its relation to age, academic marks and resolution patterns.

Abstract

In this study, we analyze learning differences in a category learning task in a sample of school children from 6 to 10 years old. We assume that children will show great differences in learning and that these differences will be related to their age, school grades and to the way they solve the task (speed and order). We assessed 432 children aged from 6 to 10 using the Category Learning Test (CLT). Results show that age is quite related to learning: in general, older children learn more than the young ones, but there are old children that do not learn and young children that do learn. Moreover, the level of learning achieved during the task is related to the way children try to solve the task. Children who respond slowly and orderly achieve a higher level of learning in the task. However, we did not find relation between the level of learning achieved in the task and children's academic marks. Finally, we carried out a regression analysis which showed that speed, organization and age predict learning in a 37,5%. The results suggest that obviously age improves cognitive ability and therefore the level of learning. In addition, the level of learning achieved depends on the way children solve the task. We discuss the impact of these findings on the promotion and improvement of learning in schools.

INTRODUCTION

The learning process or the acquisition of knowledge has been extensively studied ([Derry, 1990](#), [Novak and Gowin, 1984](#), [Anderson, 1976](#), [Kuhn, 2001](#)). Knowing this process is necessary in order to solve the difficulties that some children experience in school. Thus, the objective of this work is to determine on which variables depends the performance of schoolchildren in a learning task. We will study this process in a category learning task.

Category learning

Category learning is a type of basic learning. It is essential to establish a proper adaptation to the context and therefore to achieve school success ([Rabi & Minda, 2014](#)). The act of classifying into categories the stimulus and contexts give us information about all the elements that suit in a category. This process allows us to learn by generalization and transference the functional relations of other elements that belong to the same category. Thus, the learning process allows us to identify to which category a stimulus belongs and to distinguish a category from another (e.g. animals and humans, maritime and land transports, food and non-food items, etc). When we adequately classify we can predict how the elements within the category will act and how can we relate with each element ([Hammer, Diesendruck, Weinshall & Hochstein, 2009](#)). For example, it is not necessary to know each and every one cat to tell if a certain animal is a cat or to predict how will one cat act. We just need to know the characteristics of the species.

Different authors have used objective tests to assess category learning in children, young people and adults. In short, the most studied variables are the cognitive development of children ([Hammer et al. 2009](#); [Minda, Desroches & Church, 2008](#); [Huang-Pollock, Maddox & Karalunas, 2011](#); [Rabi & Minda, 2014](#)), and the execution variables while solving the category learning tasks ([Santacreu & Quiroga, 2016](#)).

Cognitive development and its relation to category learning

Several authors have studied the relation between cognitive development and performance in category learning tasks. To this end, they compare the results obtained by children of different ages and adults in objective learning tests.

First, [Hammer et al. \(2009\)](#) carried out a study that consists of two phases: training and assessment. During the training phase, they displayed sequentially pairs of elements that could belong either to the same category or to a different one. Researchers previously informed participants about the training procedure. Therefore, one group of participants saw pairs knowing that the elements belonged to the same category and the other group saw other pairs knowing that the elements belonged to different categories. During the assessment phase, participants had to decide if two random elements belonged to the same category or not. They assessed 20 children aged from 6 to 9.5, 20 children aged from 10 to 14 and 40 adults with this method. Results show that, within group of participants that saw pairs of the same category during the training, the three age groups reached the same level of learning. However, within the group that saw pairs of different categories during the training, the children aged from 6 to 9.5 performed worse than the other age groups. Also in this condition, children from 10 to 14 performed as well as adults. The authors conclude that the process of showing pairs of the same category promotes the learning of the category. Regarding to age, the results show that the older the children, the higher level of learning achieved. Moreover, in this study the children aged from 10 to 14 performed as well as adults in every group, which could mean that category learning is completely developed at 10 years old.

[Minda et al. \(2008\)](#) compared the performance of children in category learning tasks that differed in the degree of complexity. Seventy-seven children of 3, 5 and 8 years old and twenty four adults formed the sample. They found that 3 years old children were not able to discriminate categories in any level of complexity. In contrast, children aged 5 and 8 learned categories when the complexity degree was low (when the category classification criteria concerned only one characteristic of the element such as color). When the complexity degree increased and the classification criteria concerned more than one characteristic of the element (for example, size, color and shape) only the adults could discriminate the categories. These results pointed out that the category learning process is developing between 5 and 8 years old, what matches up with the findings of [Hammer et al. \(2009\)](#).

Similarly, [Huang-Pollock et al. \(2011\)](#) assessed the performance in category learning tasks of different degrees of complexity. 18 children from 8 to 12 years old and 43 adults formed the sample. As in the previous study, the elements of the task of low complexity learning differ in a single characteristic, while the elements of the complex tasks differ in more than one characteristic. Results showed that the level of learning achieved depends on the level of complexity of the task. On the other hand, children never reached the level of learning that adults did. So in the study it is also confirmed the parallelism between the cognitive development and the development of the category learning process.

Lastly, [Rabi & Minda \(2014\)](#) assessed 99 children from 4 to 11 years old and 56 adults through a low complexity category learning task. They analyzed the differences between the following five groups: 4-5 years old, 6-7 years old, 8-9 years old, 10-11 years old and adults. They found that the children aged from 4 to 5 and from 6 to 7 performed significantly worse than the other groups. On the other hand, the group of

children from 10 to 11 showed a similar performance than the adults. Taking these results into account we could deduce that the performance in a category learning task improves from 8 to 10 years old, time when the performance is similar to adults' one. These findings are in the same direction than the previous studies, although in this investigation children under the age of 8 are not able to learn categories, in contrast to [Minda's et al. \(2008\)](#) study.

In general terms, the results of the mentioned researchers show that category learning improves with age. Most of these studies manifest that children between 5 and 10 years old are able to solve low complexity tasks but they do not reach the adult's level of precision. Children over the age of 10 attain similar performance than adults in low complexity task but adults solve high complexity task better than these children.

Nevertheless, there are some contradictory results about middle-aged children: [Rabi and Minda \(2014\)](#) found that children under the age of 8 are not capable of learn categories in a low complexity task whereas [Minda et al. \(2008\)](#) found that children between 5 and 8 years old have the capacity to learn. Despite this inconsistency, it is clear that category learning improves over the cognitive development but the periods of the progress remain unclear.

On the basis of the data presented, the children's performance in a new category learning test should improve with age, but it is still necessary to clarify the steps of the category learning development process.

Execution patterns during the task and category learning

The differences of performance in a category learning task could be also related to the way children solve task. The execution variables in the resolution of a category

learning task that have been studied so far are the response speed and the organization of the response sequence in complex tasks.

[Santacreu and Quiroga \(2016\)](#) assessed 450 schoolchildren aged from 7 to 12 by an objective category learning task (Category Learning Test, CLT). The CLT records each participant's click in real time. Therefore the test assesses the individual's execution pattern during the resolution of the task. The task displays figures that belong to different categories and participants must identify and learn which category is associated to the highest prize. Results showed that some children did not learn to select the prize category despite that the complexity was low (the prize category consist of four-legged animals). The level of learning reached differed significantly between the children: some children learned quickly since the first trials; some children learned progressively during the task and some children did not manage to learn during the 8 trials of the task. The level of learning correlates significantly with the execution variables studied: organization ($r = 0.675$) and speed (interval between responses, $r = 0.533$).

In short, participants who don't learn the categories in the CLT respond faster and in a less organized way when trying to solve the task. The authors consider that these children probably will behave in this way in their academic tasks and therefore their school performance will be low.

Unlike other category learning tasks, the [Santacreu and Quiroga's](#) test is designed and configured to assess not only the level of learning achieved but also the execution patterns that participants display during the task. In every trial, there are simultaneously 150 elements, of which 30 belongs to the prize category. This manner of stimulus presentation, in contrast to serial one, let the participant explore around the screen during the time of the trial. The simultaneous presentation of all the stimuli

allows us to assess the level of organization of the participant's clicks and the time between them. Besides, the CLT allows the participant to execute a variable number of responses during the trial so it is possible to arise different patterns of response between participants. Additionally, this configuration gives more ecological validity to the task because of its similarity to real life, where elements appear together with others and the response options are not dichotomous but multiple and variable.

Implications for school learning

As mentioned, category learning is crucial to relate adaptively with the context so it is essential to achieve school success ([Rabi & Minda, 2014](#)). We consider that when comparing peers of the same age, those who have difficulties to learn in a category learning test could show also difficulties in school learning.

When assessing children of the same age with a category learning task, the performance should depend on the children's cognitive development or intelligence. Besides, several authors such as [Roth et al. \(2015\)](#) or [Soares, Lemos, Primi and Almeida \(2015\)](#) pointed out that the relation between intelligence and academic performance has been clearly established. That's why we expect that children who show difficulties in a category learning task could also have difficulties in their academic life.

However, published works so far have not studied through objective tests the learning differences between peers of the same age. Nor we find papers that study the relation between performance in objective learning tests and academic outcomes. That's why this paper aims to address this gap in the literature studying the possible relation between the level of learning reached in a category learning task and the academic results of the participants. Moreover, it is possible that children with inadequate

execution patterns while solving the task reproduce these problems in school, being that the reason of their low academic performance.

Aims of this research

In this study, we plan to check if learning differences depend on children's cognitive development and/or on the way they solve the task (execution patterns). In addition, we aim to analyse if the level of learning achieved in CLT is related to school performance.

In order to carry out this study it is necessary to recruit a large sample of schoolchildren of different phases of development to observe the relation between category learning and age. In addition, the sample must have participants of each age or academic grade to study if learning differences are associated to academic results within a group of peers of the same grade.

Obviously, it is indispensable a category learning test that records execution patterns (response speed and organization). The records of the sequence of participant's responses during the trial allow us to analyse the execution patterns. For this reason, we will use a version of the Category Learning Test (CLT) in the present study. Thus, we aim to answer the following questions:

1. To analyse the learning differences of the sample. The hypothesis is that in our sample, differences reached in the level of learning will be large as in the mentioned studies. If learning differences is confirmed, we will study the next topics. If the presence of learning differences is confirmed, we will study the next topics.

2. To analyse if learning differences are related to age. Our hypothesis is that older children will reach a higher level of learning than young children, according to previous studies.

3. To analyse if learning differences are related to school performance. Our hypothesis is that student's academic performance (marks) will be positively correlated to the level of learning reached in the task.

4. To analyse the relation between learning differences and participant's execution patterns during the task. We expect that children who work slowly and in an organized way will reach a higher level of learning. Thus, we expect to find a negative correlation between learning and response speed and a positive correlation between learning and organization.

5. Finally, we aim to identify on which variables depends the level of learning reached in the CLT. For this reason, we will analyse the predictive power of cognitive development variables (age and academic marks) and of execution variables (speed and organization) through a multiple regression analysis.

Method

Participants

Participants were 432 primary school children aged from 6 to 10. From these, 214 were girls and 218 were boys. Specifically, the sample consisted of 33 girls and 25 boys of 6 years old; 48 girls and 65 boys of 7 years old; 56 girls and 56 boys of 8 years old, 52 girls and 51 boys of 9 years old and 25 girls and 21 boys of 10 years old. All of them were enrolled in primary education in a charter school in Madrid at the time of the test.

Measures

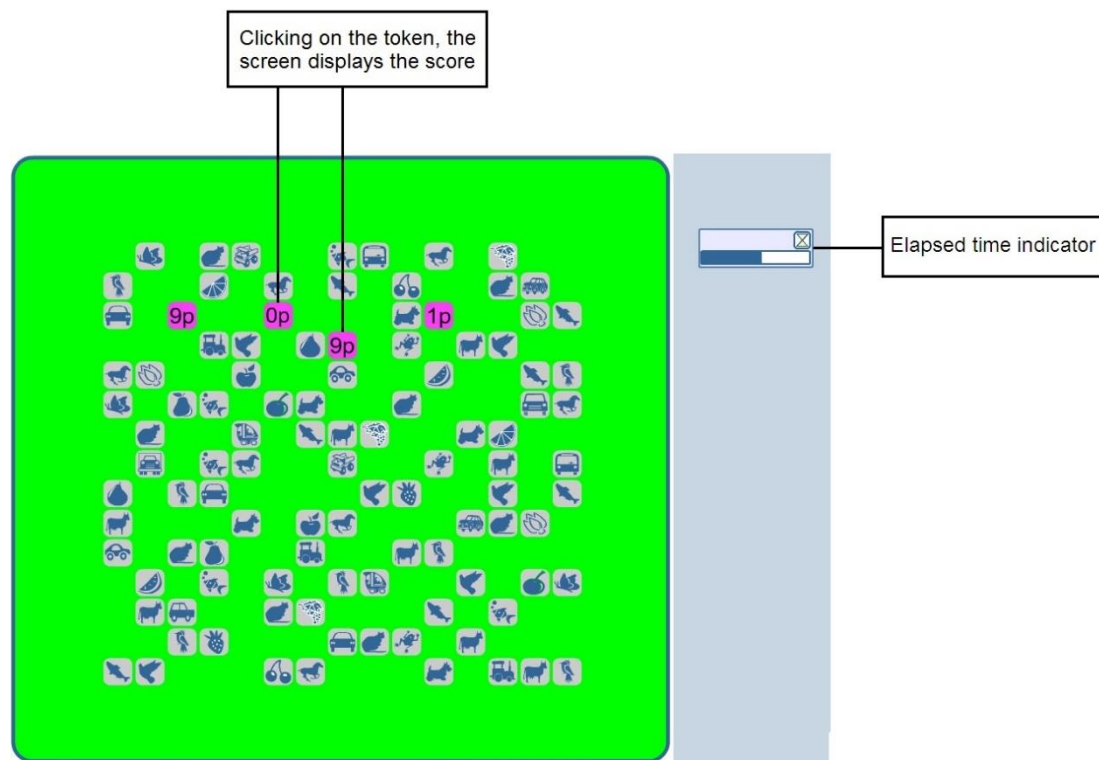
Participants completed a version of the Category Learning Test (CLT, Quiroga, Santacreu, Montoro, Martínez-Molina and Shih, 2011). As Santacreu and Quiroga indicate (2016), the CLT is a task where children must learn to discriminate which category of figures is associated with the highest prize.

The task consists of eight trials and each of them lasts 14 seconds. This version is shorter than the one used by Quiroga and Santacreu (2016) because we thought that 14 seconds per trial is time enough to assess learning. Each trial consists of a 15 by 15 matrix (225 squares or tokens) on which 105 figures of different types are in such a way that, when clicked on immediately show the amount of points obtained (9, 3, 1 or 0 points). This matrix contains 30 tokens featuring four legged animals (tokens with a value of 9 points) and 75 tokens featuring other figures (21 tokens worth 3 points, 20 tokens worth 1 point and 34 tokens with a value of 0).

Figure 1 presents a CLT's item where it is showed that when clicking on the token, the screen displays the associated score. The timer is present in every item on the right side of the screen.

Insert Figure 1 about here

Figure 1. Example of a CLT's item where four different tokens have been clicked on



The CLT registers the click type (which figure is clicked on) and when the click occurs. From these data it provides the following variables: 1. Hits (H, mean number of 9-point tokens clicked on); 2. Errors by commission (CE, number of clicks, per trial, on tokens that do not carry 9 points); 3. Task Organization Index (TOI, sequence and order in which the screen is scanned); 4. Learning Index (LI, ratio of hits to the total number of clicks); and 5. Speed (number of clicks per second).

To complement this information, we asked the school for information about the average marks obtained by each child in the grade that they were about to finish in the moment of the test.

Procedure

First, the participants' legal tutors were informed about the study and signed informed consent document allowing their children to participate in the investigation.

Participants completed the task during school time on the latest days of the academic year. They were divided into groups of maximum 25 children in order to have one computer per children in the IT room and to be properly supervised. Three psychologists checked that everything worked properly. Before starting the task, instructions were projected on a big screen waiting until everyone had understood. The instructions indicate that the aim of the task is to identify and click on figures associated with the best prize to get the highest score.

Once the data was recorded, each child's scores were calculated for each trial. Statistical analysis was performed using SPSS Statistics 22.0 package.

Results

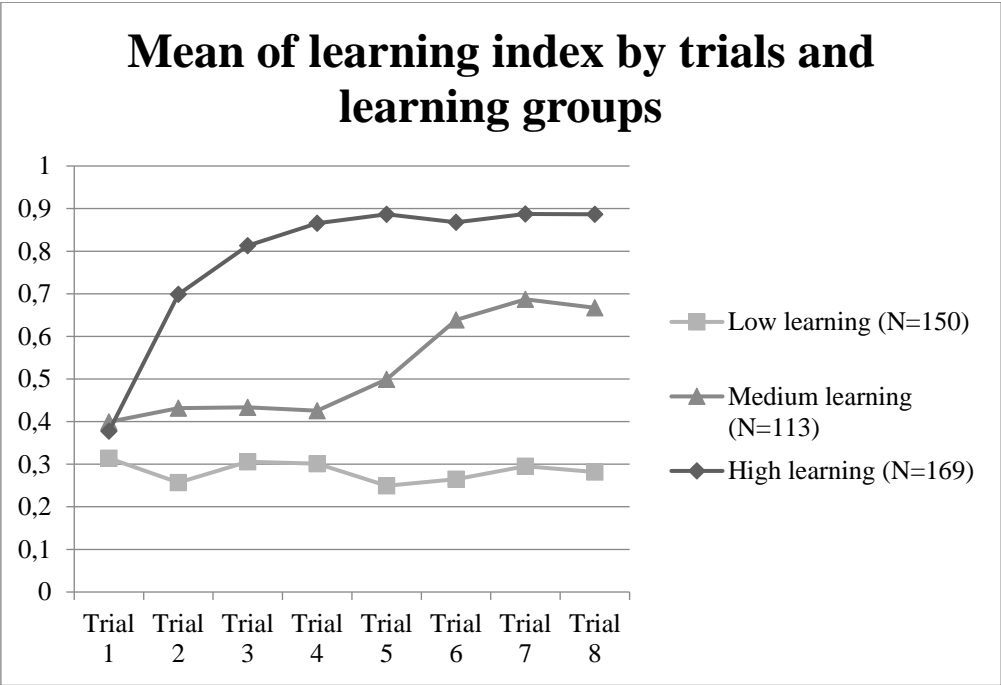
Regarding to the first hypothesis, the learning progress along trials was analysed in the whole sample. The learning index (LI = ratio of hits to the total number of clicks) of the whole sample increases along trials from a LI=0.36 on the first trial to a LI=0.62 on the last one. The standard deviation (SD) in every trial is very high ($0.32 < SD < 0.35$), what indicates that there are considerable inter-individual differences.

Because of these wide inter-individual differences, a cluster analysis of profiles (SPSS K-Means procedure) was carried out to identify if there are diverse groups with different modes of learning. The cluster analysis took into account the level of learning achieved in every trial and classified participants in three different groups. As figure 2 shows, the Low Learning Group (LLG) is formed by 150 people (75 girls and 75 boys) that seem not to learn anything along trials, they start the task with a learning index (LI) of 0.31 and they finish it with a LI of 0.28. The High Learning Group (HLG) formed by

169 children (54 girls and 59 boys) that quickly learn from the first trial. In the second trial, they reach a LI = 0.70 that continues slightly increasing until the last trial when their rate of hits is LI=0.89. The Medium Learning Group (MLG), formed by 113 children (85 girls and 84 boys) learns slowly and progressively along trials. They start the task with a LI=0.39 and finally ends with a LI=0.67.

Insert Figure 2 about here

Figure 2. Mean Learning Index by trial and learning groups



Once the differences in the learning patterns of the students were confirmed, we analysed the effect of age on the performance of the test. Table 1 shows means and standard deviations of learning in each age group. The ANOVA test shows the significant differences among the age groups. These results suggest that the older children learn more than the young ones. We carried out a Student’s t-test to analyse differences between each age group and its contiguous. Student’s t-test results indicate significant differences in learning among 7-aged group and 8 aged group ($t=5.857$,

$p<.001$) and also among 9 aged group and 10 aged group ($t=1.989$, $p<.05$). Nevertheless, there are not significant differences between ages 6 and 7 nor between ages 8 and 9. Obviously, differences between non-contiguous age groups are significant. Old children learn the most and young children learn the least.

Table 1. Mean and Standard Deviation of Learning Level by age groups. ANOVA shows significant differences between the groups

	Age 6 (n=58)		Age 7 (n=113)		Age 8 (n=112)		Age 9 (n=103)		Age 10 (n=46)		ANOVA
	M	SD	M	SD	M	SD	M	SD	M	SD	F
Learning	0.38	0.18	0.43	0.23	0.60	0.22	0.64	0.20	0.70	0.19	33.358*

* $p<.001$

However, the learning index' standard deviation is very high in every age group ($0.18>SD>0.23$) what means that children in one age group have quite different learning levels. A new analysis was carried out in order to check if the three learning profiles (low, medium and high learning) are present and have a similar ratio in all ages. Results show that in all ages there are participants that quickly learn and reach a high level of learning, participants that learn progressively and others that do not learn (see table 2). Namely, the three learning profiles are present in all ages. However, in our sample, the ratio of kids that achieve a high level of learning is larger in the old children groups (54% and 67%) than in the young groups (10% and 18%). The Chi-squared test indicates that there are significant differences in age distribution among the groups ($\chi^2=100,377$, $p<.001$). The table 2 could be presented splitting children by academic grade rather than by age and the distribution would be equivalent.

Table 2. Learning groups by age. Frequency and percentage.

	Age				
	6	7	8	9	10

Low learning (N=150)	40 (69%)	60 (53%)	31 (28%)	15 (15%)	4 (9%)
Medium learning (N=113)	12 (21%)	33 (29%)	25 (22%)	32 (31%)	11 (24%)
High learning (N=169)	6 (10%)	20 (18%)	56 (50%)	56 (54%)	31 (67%)
Total participants	58 (100%)	113 (100%)	112 (100%)	103 (100%)	46 (100%)

To analyse the relation between the academic grades and the LCT learning index, we compared the grades of children between peers in the same grade. We divided the sample into four groups based on their academic grade: 1st grade (equivalent to 6-7 years old), 2nd grade (7-8 years old), 3rd grade (8-9 years) and 4th grade (9-10 years). In each grade, we can find children in the LLG, in the MLG and in the HLG as we have seen in the table 2. So, the mean of the marks for every learning group in each grade appears in table 3. ANOVA analysis was carried out and the results showed that there are not significant differences in academic marks between the learning groups. Moreover, in every grade, correlations between academic marks and learning index are very low and not significant. Contrary to expectations, children that obtained better academic marks do not learn more in the category learning test than the other children do.

Table 3. Mean of academic marks by grade and learning group and ANOVA analysis.

	Grade			
	1 (N=116)	2 (N=118)	3 (N=106)	4 (N=92)
Low learning (N=150)	7.42	7.55	7.68	7.98
Medium learning (N=113)	7.40	7.33	7.80	7.31
High learning (N=169)	7.26	7.75	7.46	7.49
Total Grade	7.40	7.56	7.60	7.48
ANOVA F - p	0.203 – 0.817	1.760 – 0.177	1.081 – 0.343	1.797 – 0.172

The aim of the fourth question is to find out the importance of the execution variables (organization and response speed) in the learning index of the test. To describe the different patterns of the three learning groups table 4 shows means and standard deviations of: organization, speed, hits, errors and learning index. The ANOVA analysis shows that there are significant differences between the three groups in all the variables. T-test showed that these significant differences are present between all the groups, except for organization where there are not significant differences between the medium and high learning groups. The results indicate that participants of the LLG, clicks on a larger number of tokens than the other groups and does it on a speedier way. Nonetheless, most of clicked tokens are associated to a low score (errors). The organization is lower in the LLG. Moreover, the correlation between learning index and speed is significant and negative ($r=-0.205$, $p<.01$) and between learning index and organization is significant and positive ($r=0.252$, $p<.01$).

Table 4. Means and SD of CLT variables. Data from ANOVA analysis showing significant differences between the groups.

Index	Groups						ANOVA	
	Low learning group (N=150)		Medium learning group (N=113)		High learning group (N=169)		F	p
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation		
Learning*	0.28	0.09	0.52	0.08	0.79	0.09	1322.341	0.000
Organization^{1,2}	1.85	2.57	3.08	3.07	3.27	2.96	14.13	0.000
Speed^{2,3}	0.55	0.3	0.49	0.23	0.44	0.17	8.905	0.000
Hits*	2.04	1.12	3.30	1.57	4.71	1.92	112.24	0.000
Errors*	4.09	2.11	2.80	1.51	1.08	0.73	154.19	0.000

1= significant differences among groups of low and medium learning

2= significant differences among groups of low and high learning

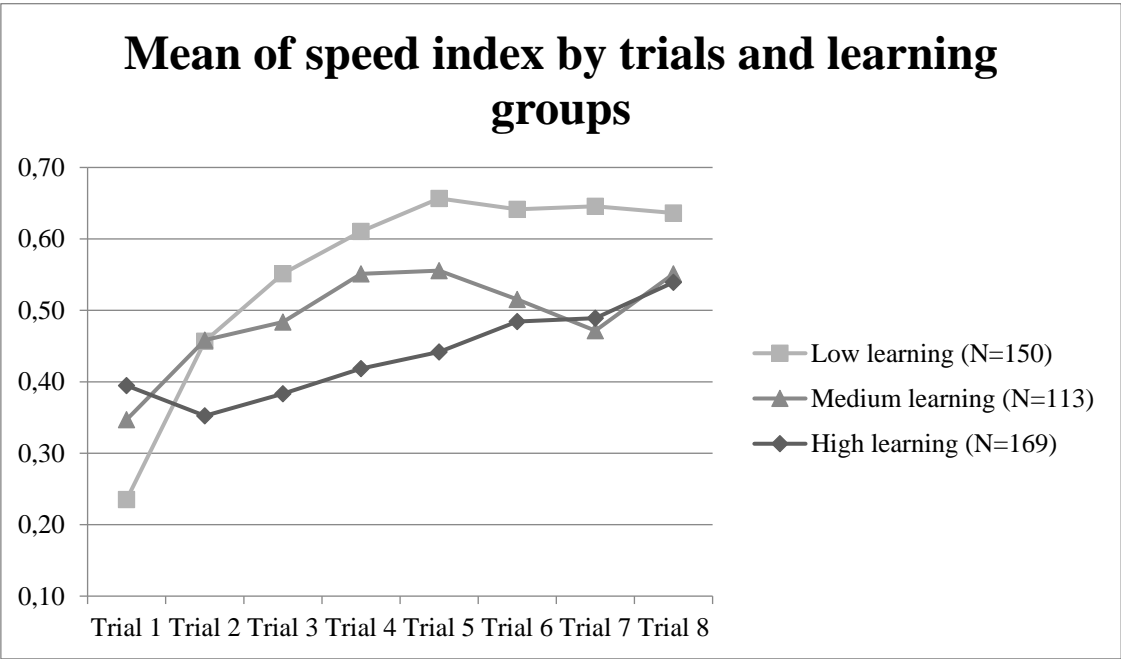
3= significant differences among groups of medium and high learning

*: significant differences among the three groups

We analysed the evolution of the variables related to the execution patterns (speed and errors). As shown in figures 3 and 4, the low learning group is the fastest clicking on the tokens. That group clicks on more tokens each trial but also commits more errors (by clicking on tokens with a low prize) in every trial. So, the group that learns the least starts in the first trial with a Speed Index of 0.17 and an Errors Index of 1.82 and ends the task with a Speed Index of 0.44 and an Errors Index of 4.53. The other two groups behave different, their response speed increases less and their errors decrease notably. It should be noted that the group that learns progressively, decrease its speed and errors by the second half of the task, moment when the group increases its learning index and score.

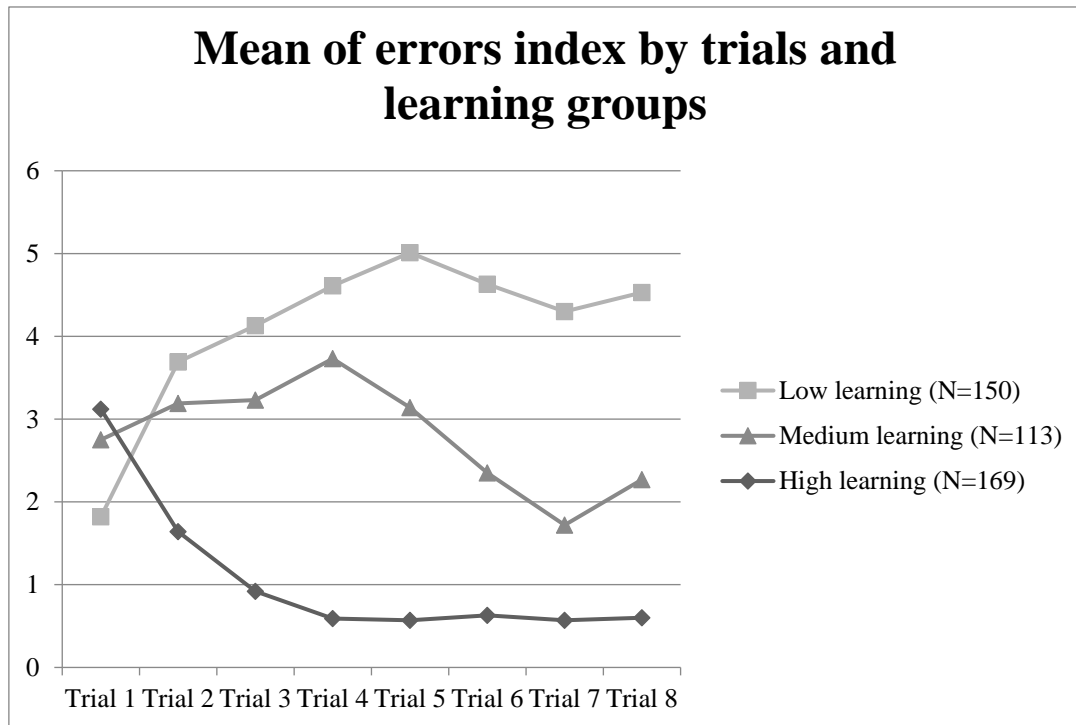
Insert Figure 3 about here

Figure 3. Speed index by trials and learning groups.



Insert Figure 4 about here

Figure 4. Errors index by trials and learning groups.



Concerning the last hypothesis, to find the predictive power of cognitive development and execution variables over learning, we completed a multiple regression analysis (stepwise procedure) to identify which variables predict learning (LI): age, academic marks, speed and/or organization.

Table 4. Summary of the hierarchical regression analysis for variables that would predict the learning index (LI) in the CLT (N = 432).

Step and predictive variable	B	SEB	β	R ²	ΔR^2
Step1					
Age	0.090	0.008	0.468	0.219*	-
Step 2					
Age	0.117	0.008	0.608		
Speed	-0.389	0.040	-0.410	0.367 *	0.148*
Step 3					

Age	0.110	0.009	0.568		
Speed	0.397	0.040	-0.418		
Organization	0.009	0.004	0.100	0.375*	0.008*

*p<.05

Table 4 include the variables and beta coefficients for each step. The analysis only used the variables age, speed and organization and the total adjusted R^2 obtained was 0.375. The data in Table 4 show that the organization and speed for completing the task and the age of the participant predict the differences in learning index.

DISCUSSION

Firstly, and regarding the first hypothesis, we observe a high variability in the results attained in the Category Learning Test. 34.7% of children between 6 and 10 years old do not learn in this test: we can see that they do not improve their ratio of hits (clicks on tokens associated to the highest prize) during the task (see figure 2). In contrast, 39.1% of sample participants learn very quickly from the first trials and they maintain a high ratio of hits during the task. The remaining 26.2% of children learn progressively, reaching a high ratio of hits in the last trials. Therefore, the data confirms our first hypothesis: there are large differences in the level of learning reached by the participants, some participants learn and others do not.

Based on the results of [Hammer et al. \(2009\)](#), [Minda et al. \(2008\)](#), [Huang-Pollock et al. \(2011\)](#) and [Rabi & Minda \(2014\)](#), the existent learning differences could be related to the participants' cognitive development. According to these results we expected that the group of children that cannot solve the task would be young children. Therefore, we analysed the relation between learning differences and participants' age. Indeed, comparing the different age groups, we found that older children (10 years old)

learn more than middle children (8-9 years old) and these learn more than youngest children (6-7 years old). Hence, participants' age is related to the level of learning achieved. However, age is not the only factor that explains the learning differences. In the youngest group there are children that achieve a high level of learning and within the older group there are children that do not learn. So, we investigated other variables that could influence learning.

Regarding the third hypothesis we expected a positive relation between learning and participants' academic results under the assumption that academic marks will correspond with the level of cognitive development in children of the same age and grade. Nevertheless, results show no significant relation between learning and academic marks in any academic grade.

The low level of variability of the children's academic mark can explain this unexpected results. Mean of this variable is 7.5 points (out of 10) and standard deviation does not reach one point ($SD=0.89$). The low variability of the data prevents a high and significant correlation between variables. This lack of variability may be because the basic education is planned for every student being able to attain the goals of the course. Perhaps the academic marks will vary more in higher education so we could observe their relation to category learning. Additionally, some authors pointed out that the relation between intelligence and academic results is higher in certain subjects such as maths or science (Furnham & Monsen, 2009). We use the average of all subjects including gymnastics, music or art, which will explain the low correlations obtained. Hence, it would be convenient to investigate in future studies the relation between performance in the Category Learning task and the marks in specific subjects such as maths, in which learning difficulties frequently arise (Blair & Razza, 2007).

Moreover, in future studies it could be useful to assess cognitive development by another variables than academic marks. [Heaven and Ciarrochi \(2012\)](#) pointed out that children's academic results depend not only on intelligence but also on other factors such as personality. In future studies, in order to find the cognitive development influence on learning processes it would be convenient to use direct measures of cognitive development. We propose to measure cognitive development through cognitive tests such as intelligence, memory or reasoning test instead of estimating it through academic results.

Regarding execution patterns we expected, as well as [Santacreu y Quiroga \(2016\)](#) founded, that children who work slowly and organized would attain a higher learning level. Therefore, we hypothesised a negative correlation between speed and learning and a positive relation between organization and learning. We found that in fact the group that does not learn (LLG) acts speedier than the groups that do learn. Besides, this group increases its speed along the trials, clicking in more tokens each trial and increasing the number of errors (see figures 3 and 4). In contrast, the group that learns progressively along the trials (MLG) decreases its speed since the fourth trial, decreasing its errors and improving its learning index since that moment. MLG, unlike LLG, seems to be able to regulate their performance in order to optimize their learning. Lastly, HLG increases its speed from the third trial when it already knows which tokens are associated to the best prize as we can see in its learning index. Thus, HLG can achieve more hits without increasing the number of errors. Anyway, HLG's speed stays always lower than LLG one.

With respect to organization, LLG shows lower organization than the groups that learn. This group clicks on the tokens not following an order of rows and columns, what seems to interfere with its learning.

As we expected, correlation between learning and execution indices is significant, being negative in speed index and positive in organization index. However, correlations found in this study are lower than in [Quiroga and Santacreu's one \(2016\)](#). We may explain these results because we have used an abbreviated version of the CLT in which each trial lasts 14 seconds instead of 21. Although it is possible to observe learning differences with the abbreviated version, participants had not time enough to show large individual differences in execution patterns so correlations of these variables decrease.

In any case, results about execution variables show that the low learning group is not able to regulate adequately its speed and the sequence of their responses to optimize its learning. When they respond quickly and make mistakes, they do not increase their latency to improve their performance.

Lastly, regression analysis was carried out to know the learning predictive power of cognitive development variables (age and academic marks) and execution variables (speed and organization). Results show that the most relevant predictor variables are age, speed and organization. Academic marks do not contribute to improve the regression model as might be expected based on its correlation with learning. Consequently, children will achieve a higher level of learning if they are older, work slowly and in an organized way. These results match with those found by [Hammer et al. \(2009\)](#), [Minda et al. \(2008\)](#), [Huang-Pollock et al. \(2011\)](#) and [Rabi and Minda \(2014\)](#) with respect to age, and with [Quiroga and Santacreu \(2016\)](#) regarding to the relevancy of response speed and organization.

Implications for school learning

On the one hand results show that category learning improves with age, from 6 to 10 years old, as expected on the basis of the mentioned studies. However, we observe that learning differences are not due only to age but also to the way children solve the task. Those who are capable to act slowly and in an organized way attain a higher level of learning than the others. Moreover, children of MLG show that when decreasing their speed, they are able to decrease its errors and improve their learning.

This seems to be related to self-regulated learning models, that highlight the self-observation of performance as a relevant component whereby the student notices his achievement being able to improve it (Schunk & Zimmerman, 2003). Similarly, some authors underline the need for the apprentice to be able to monitor their learning , self-assessing and to pay attention to feedback in order to solve their errors (van Loon, Destan, Spiess, de Bruin & Roebbers, 2017). This self-monitoring skill improves when children mature because they are fitted to estimate more accurately their hits and errors (van Loon, de Bruin, Leppink, & Roebbers, 2017; Finn & Metcalfe, 2014). Nevertheless, on the basis of the results of the present study it seems that at the age of 10 there is still a wide percentage of children who cannot self-monitor their own learning.

Regarding this learning model and the relation between speed, organization and learning, in future studies it could be useful to check if an intervention to promote self-monitoring and therefore slowness and organization (for example, self-instruction procedure by Meichenbaum, & Goodman, 1971) improves the children performance.

It is crucial to investigate which factors optimize category learning and which ones block it as these variables could influence on school learning. Despite in this study we have not found relation between academic performance and learning in the task, we think this could be due to the use of the mean of all the subjects' marks (including

gymnastic, arts, etc.) or to the lack of variability of the marks in the studied school stage. Therefore, in future studies we expect to find relation between performance in CLT and academic marks in high education stages and in specific subjects such as maths or science.

To this aim, we highlight the relevance of assessing learning through objective computerized tasks that record accurately the temporal sequence of the responses and which configuration permits participants to show their personal execution pattern. Thanks to this record we have found that learning differences are related not only with age but also with the execution patterns. This is of great importance because we have found which resolution pattern promotes learning in a category learning task: a slow and organized performance.

Limitations

Firstly, in the present study we have studied learning only in children from 6 to 10 years old. It would be interesting to have information of older children and adults' execution to observe when in the development category learning is established.

On the other hand, as mentioned, it would be helpful to study the relation between learning in CLT and performance in specific subjects as maths or science. Besides, it would be useful to possess direct measures of cognitive development such as intelligence, memory or reasoning tests to study its relation to category learning.

Lastly it would be desirable to use a non-abbreviated version of the CLT in order to study adequately the relation between learning and execution patterns.

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