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## **Getting it right takes time: latency and performance in secondary school students**

### **Abstract**

The relation between response time and performance in cognitive tasks is increasingly evident, although the predictive relevance of response time compared to general intelligence or task-specific abilities has not been established definitively. In the present study, we analyzed the effect of participants' spontaneous speed when responding to a mental rotation task from both an experimental and a differential perspective. We carried out a data reanalysis from a previous study where a training of 3 practice sessions of 100 trials each was applied. The procedure was applied to a sample of 21 high school students (11 boys and 10 girls). The relation between response time and performance (hits) across the training trials was analyzed. In addition, we carried out a regression analysis of performance on the learning task as a function of response time on that same task along with the score on two previously applied tests of spatial intelligence (EFAI) and fluid intelligence (RAVEN). Results showed, a) a significant relationship ( $r=.624$ ) between response time and hits, b) that the group of participants with longer response latencies performed better; c) that participants' response time explained most of the variance of their score on the training task in the regression analysis, although spatial and fluid intelligence scores improved the prediction of performance. The results and their implications are discussed.

**Keywords:** Response Latency; Time Factors (Learning); Performance; Visuospatial Ability; Intelligence; Individual Differences

## **Getting it right takes time: latency and performance in secondary school students**

One of the most interesting lines of research in psychology in the last hundred years has tried to decipher why there are differences in the level of learning achieved in a given task. To answer the question "why do only certain individuals learn when performing a certain task?", the problem has been approached from behaviorist (research initiated by John B. Watson, 1913) or cognitivist (see Rivi re, 1991 for a review) approaches. The answer implies characteristics that are supposed to be relatively stable in individuals, such as the level of intelligence. Another question has arisen in these terms: "what characteristics of the learning tasks make them be easy or difficult?" Nowadays, how to order learning tasks by degree of difficulty is well known. The most attractive question now is "what variables, in addition to those of the individual and those of the task, are involved in learning?". The answer is that every learning process is an interaction between the characteristics of the person and those of the task (for a theoretical and methodological review, see Hern ndez, 2000; Author et al., 1999). What we call interaction is the person's way of acting, their behavior when performing the task; and it is observed through the so-called "performance factors" of the task (Goldstein et al., 1990), among which are considered those related to what and when each person responds.

Traditionally, the time that individuals take to respond (reaction time, latency or response time) has been studied as a function of other more complex cognitive processes that would mediate between the stimulus and the response to a cognitive task (Goldstein et al., 1990). An example of this category, of great interest for the studies that we present in this work, is the classical study by Shepard and Metzler (1971) on response times and angular disparity in a Mental Rotation task. In this work, the authors presented pairs of figures in different orientations. Some figures were identical but rotated and others were symmetrical (mirrored) versions; the task consisted in indicating whether or not the figures were identical. What

interests us here is that the angular disparity was manipulated and the results showed that the response time was longer as the angle of rotation increased.

A key aspect in studies that analyze response times is whether the conditions of the task induce a certain speed (e.g., trials with limited time) or whether they allow the participants to work at their own pace. In the latter case, the speed at which the participant responds has been called *spontaneous speed*. De Boeck et al. (2017) analyzed the differences between tasks that allow spontaneous speed and those that restrict the time available to respond. The review of the literature shows that the effect of the so-called *accuracy speed tradeoff* has been exhaustively studied, mainly manipulating speed parameters induced by the time available to respond. However, there are very few studies on the effect of the spontaneous speed of individuals when solving a task. Some previous studies have observed that induced or imposed speed tasks have different effects than tasks in which the time to respond is not restricted (DiTrapani et al., 2016; Patchev & De Boeck, 2012). In general, tasks that allow spontaneous response speed obtain greater precision (performance) than those with imposed speed. Some studies have related the speed-accuracy trade-off to Kagan and Kogan's (1970) Reflexivity-Impulsivity (R-I) model, in which Reflexivity implies a longer response time until one is sure of choosing the correct alternative. In this sense, the most reflexive people would show greater precision and longer latencies.

Author et al. (2008) analyzed different ways of solving a dynamic spatial task (*Spatial Orientation Dynamic Test-Revised*; SODT-R) with 9 evaluation trials of 20 seconds each. The task was to change the course of a moving point so that it headed towards a destination marked on the screen. To perform the task, two buttons with right and left directions were manipulated. The results of this study showed that the response time of the first press to direct the point correctly towards the destination point allowed to discriminate between two rather opposite strategies. On the one hand, the people who took longer to respond at the beginning of the test tended to correct the trajectory of the mobile point in the correct direction, more efficiently

(with fewer clicks). On the contrary, the people who tended to respond more quickly when presented with the trial were grouped in a strategy based on trial and error, where it was more frequent that the first press would not orient the mobile point towards its correct destination. In a later study, Author et al. (2011) applied the R-I model to this finding. They studied the way in which more than 500 university graduates solved the SODT-R test. Their results supported the R-I model applied to the way of solving the spatial test, and the group of participants with a behavior identified as "reflective" showed longer latencies, but with greater precision and efficiency.

Next, we will review another series of studies that demonstrated the important role of response time in performance in a category learning task. In this type of task, the learning of concepts is evaluated based on strategies that require the participant to compare and contrast groups that contain relevant characteristics for the category with groups that do not contain such characteristics. Author et al. (2016) applied a category learning test (Category Learning Test; CLT) and an attention test (Simple Visual Tree Discrimination Test - *Discriminación Visual Simple de Árboles*- DiViSA) to a sample of 450 schoolchildren aged between 7 and 12 years. They tried to verify whether the level of attention reached in the DiViSA test would predict the level of learning in the CLT test. In the task, a series of figures were presented that awarded points. Participants had to click on those that offered the most points. The task has a total of 8 trials of 20 seconds duration each and offers feedback on the score obtained. The slope of the learning curve observed in this study indicated a very low level of learning but, at the same time, showed high individual variability; that is, there were important differences in the schoolchildren's learning rate. In the search for variables related to performance, the authors introduced the response time of the learning test into their analyses; In the regression analysis, they found that, surprisingly, the response time in the learning task explained most of the variance in the performance achieved by the students, so that the slower the response time, the better the performance in the task. Author et al. (2019) tried to replicate these results by

applying the CLT to a sample of 466 schoolchildren aged between 6 and 11 years. They divided the sample into three groups based on their performance on the CLT. The group with the greatest learning showed a greater initial latency and increased the response speed from the fourth trial onwards, after discovering which were the figures that belonged to the category with which the highest number of points was awarded. The low learning group, on the other hand, responded faster than the high and medium learning groups and failed to discover the category that optimized performance.

Author et al. (2021) replicated the above results in a sample of university students. The authors investigated whether increased response time in participants who performed poorly on the CLT task translated into improved performance. The test was modified (momentarily deactivating the mouse after each click) to increase the response time in the experimental group. The participants in the control group performed the same test with no changes. The results obtained showed that the experimental group reached a higher learning rate compared to the control group. Although many hypotheses were raised, this latest work failed to definitively explain why some participants did not slow down their response speed.

This review of previous studies highlights the relevance of the response time on the efficiency to solve experimental tasks across various cognitive abilities. However, all the studies reviewed were carried out under time restrictions, presenting trials with a limited duration that, therefore, induced responding as quickly as possible. The studies were carried out with large samples, but with a low number of trials, although each of them involved between 10 and 25 responses. Considering De Boeck et al.'s (2017) conclusions, the objective of the present study is to analyze the effect of response time under conditions of spontaneous speed, in a mental rotation task where the participants work at their own pace. To address this objective, the data from Author et al.'s (2016, 2022) sample of secondary education students was reanalyzed. Previous studies addressed the efficacy of the trained group versus a control group (Author et al. 2016) and the differences in learning by gender and level of spatial

intelligence (Author et al. 2022). In the present study, new analyses are carried out to understand which variables explain how said learning is optimized, due to the educational implications that this supposes to address future cognitive training. The context of application was a training in mental rotation over three sessions on consecutive days, with an average duration of half an hour each. There was no limited time to respond, and, after each trial, the participant was provided with feedback regarding their performance (hit or error). The present reanalysis was carried out on the training data applied to secondary school students.

Taking into account the reviewed studies, our main hypothesis is that the correlation between the response time used in the test by each participant and the performance (hits) in the spatial task will be high and significant.

Secondly, we will classify the participants according to their performance in the spatial training task using the *K-means* procedure. We expect that participants who achieve higher performance across trials (higher proportion of hits) will also show higher response times. If slowness is important for a higher proportion of hits, as we have found in the review carried out, the prediction is that the group with a greater latency will have a better mean performance throughout all the training sessions.

Finally, we will test the predictive power of the response latency variable in the effective performance of the task (proportion of hits) with a multiple linear regression analysis. The predictive power of the response time, fluid intelligence and initial spatial ability (prior to training) variables will be compared. Based on previous studies, a greater weight of general spatial ability (assessed through the EFAI-E spatial subtest) is expected due to the positive correlation found between different spatial sub-abilities (Carroll, 1993). The prediction about the predictive power of the intelligence variable is uncertain, because although the general spatial ability ( $G_v$ ) correlates with the intelligence  $g$  factor (Carroll, 1993), a high correlation between spatial ability and fluid intelligence has not always been found (Author et al. 2011;  $r < .2$ ).

## **Method**

### **Participants**

Twenty-one students (10 boys and 11 girls) from the third year of secondary education participated in the study. The mean age was 14.3 years (standard deviation 0.44). The study was authorized by the Ethics Committee of the responsible entity, complying with all regulations in this regard. All minors consented to participate, and, in addition, all legal guardians signed an informed consent.

### **Instruments**

***Spatial ability subtest “E” of the EFAI-3 (Factorial Evaluation of Intellectual Abilities; Santamaría et al., 2005)***

This test is applied between the ages of 12 and 15 years to assess the ability to perform mental transformations of objects in space. The test has 27 items that present a comparison stimulus and several response alternatives. The participant must indicate the alternative that fits with others already placed in the comparison stimulus, in order to complete the puzzle. The reliability of the test is .71. The maximum correct score is 27. The participant has six minutes to complete as many items as possible.

***Raven's Progressive Matrices (SPM; Raven et al., 1996)***

The test assesses general intelligence and can be applied from 6 years of age onwards. The test consists of 60 items, grouped into five series of 12 items that are completed without a time limit. Each item has between six and eight response options, only one being correct. The maximum correct score is 60. The split-half reliability of this test is .90.



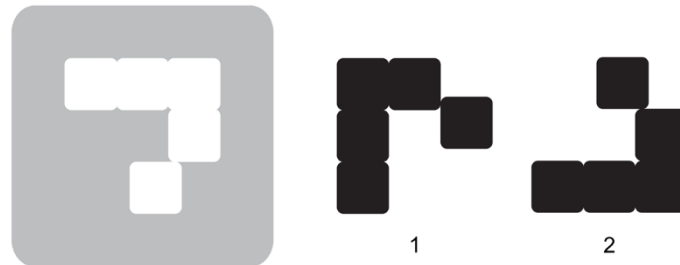
***Mental Rotation Training Program (Programa de entrenamiento en Rotación Mental, PEMR; Author et al., 2016)***

In this program, 300 assessment trials were applied, divided into three sessions. In each trial, a white mold (target) was shown on the left side of the screen and two comparison stimuli were on the right, labeled “1” and “2”. For each one, the keys marked “yes” or “no” had to be pressed to decide whether the figure fit the mold on the left. Each trial involved two mental rotation exercises (two stimuli or items per trial). The hits and the response times for the 300 trials were recorded, for a total of 600 rotation decisions (100 trials and 200 decisions or items per session).

The difficulty of the trials increased progressively both within and between sessions, due to the complication of the characteristics of the stimuli presented. The task was programmed using E-Prime version 1.2 (*Psychology Software Tools*, 2002). The variables analyzed were:

- a) the proportion of hits per intra-trial (within trial) decision (dependent variable "hits decision 1" and "hits decision 2") and the mean response time for each decision (classification variable expecting that those with higher performance will show greater response time) for the analysis of performance progression.
- b) the total mean hits (mean hits per trial between decision 1 and 2, dependent variable) and the total mean response time (mean time of decision 1 and 2, criterion variable) for the regression analysis. In the regression model, the mean hits scores in the Raven intelligence test and the EFAI-E test will also be added as criterion variables.

**Figure 1.** *Example of a PERM-Secondary trial*



### Procedure

The students completed in a first session, seated at individual tables, and using the paper and pencil test, the spatial test of the EFAI-3 and the Raven Progressive Matrices Test. Over the following three days, in sessions of about half an hour each, the adolescents completed the PERM. This task was carried out in the computer room with computers for individual use. Statistical analyzes were performed with the SPSS program, version 24.0 (IBM Corp., 2016) with a significance level of .05.

### Results

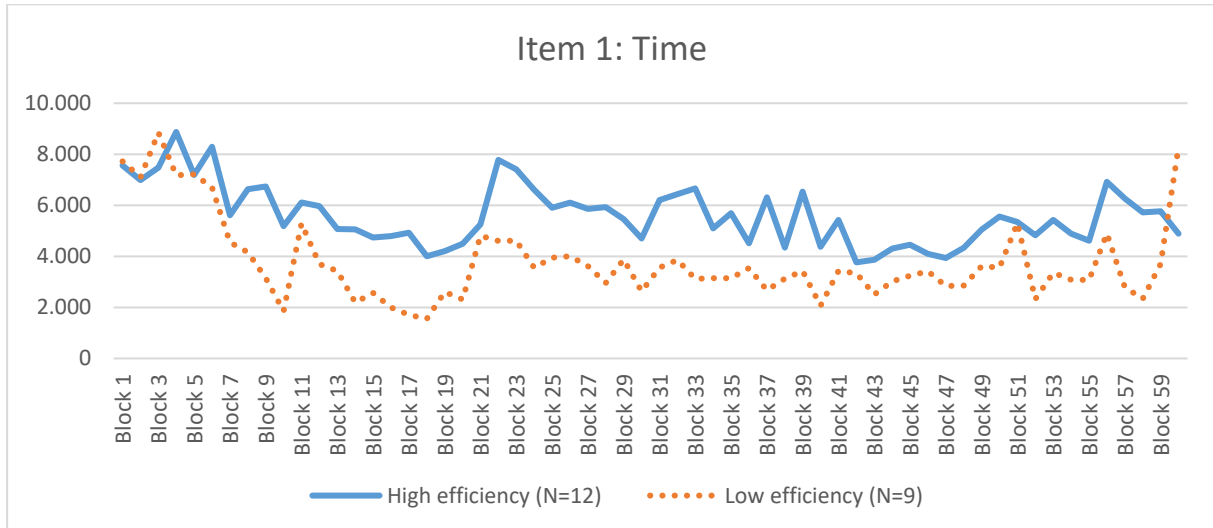
The relationship between response time and hits was  $r = .568$  for the decision of item 1 and  $r = .643$  for the decision of item 2, both significant ( $p < .01$ ). The data coincide with the proposed hypothesis. The speed with which one responds is a variable that is positively associated with performance in the task, the number of hits being higher when the response time is longer. To test the second hypothesis about the classification of groups based on response time and performance, two groups were created applying the *K-means* procedure,

according to the response time of the first item of each trial. Based on this classification, the results for the decision of item 2 are presented.

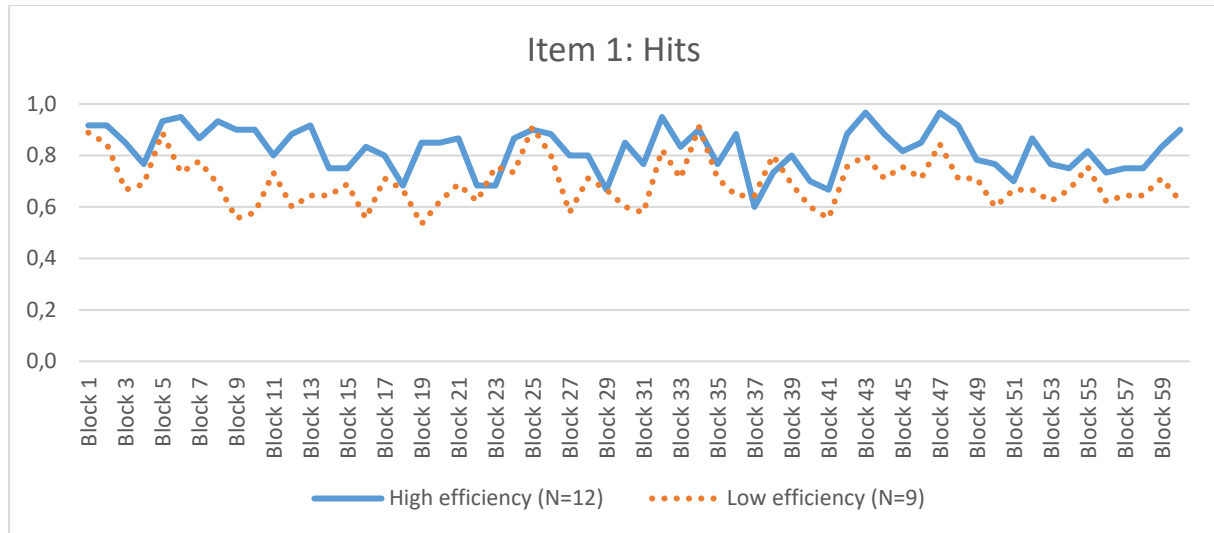
The classification by response time shows two groups: High efficiency group (longer response time) with N=12, and Low efficiency group (shorter response time) with N=9.

Figures 2 and 3 show the results of response time (in milliseconds) and hits in the total number of trials trained for the two classification groups in Task 1. Each training session corresponds to 20 blocks of trials (one block is composed of five trials and therefore the 100 trials per session form 20 blocks; in the three sessions we have a total of 60 blocks). The data from block 21 thus corresponds to the first block of the second session and 41 to the first block of the third session.

**Figure 2.** Response time for item 1 in each block of five trials, according to efficiency groups by response speed of the participants.



**Figure 3.** Hits for item 1 in each block of five trials, according to efficiency groups by response speed of the participants.

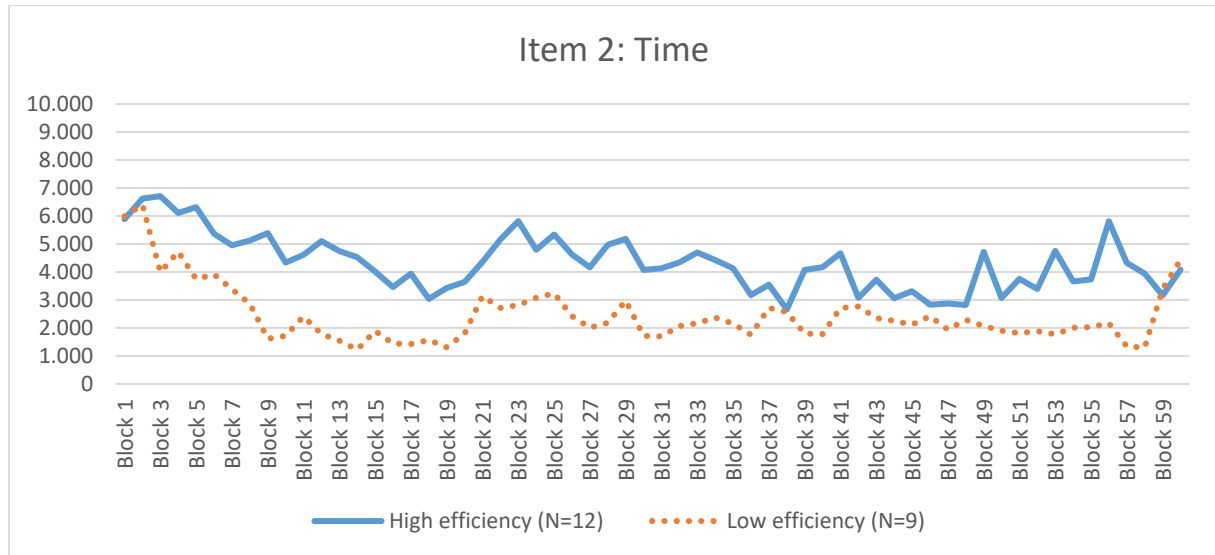


The data from the Figure 3 in blocks of five trials show that the participants can be classified into two groups according to the speed at which they respond both in item 1, through which they are classified, and in item 2. The differences between the High efficiency (slow) and Low efficiency (fast) group of participants are maintained throughout all trial blocks.

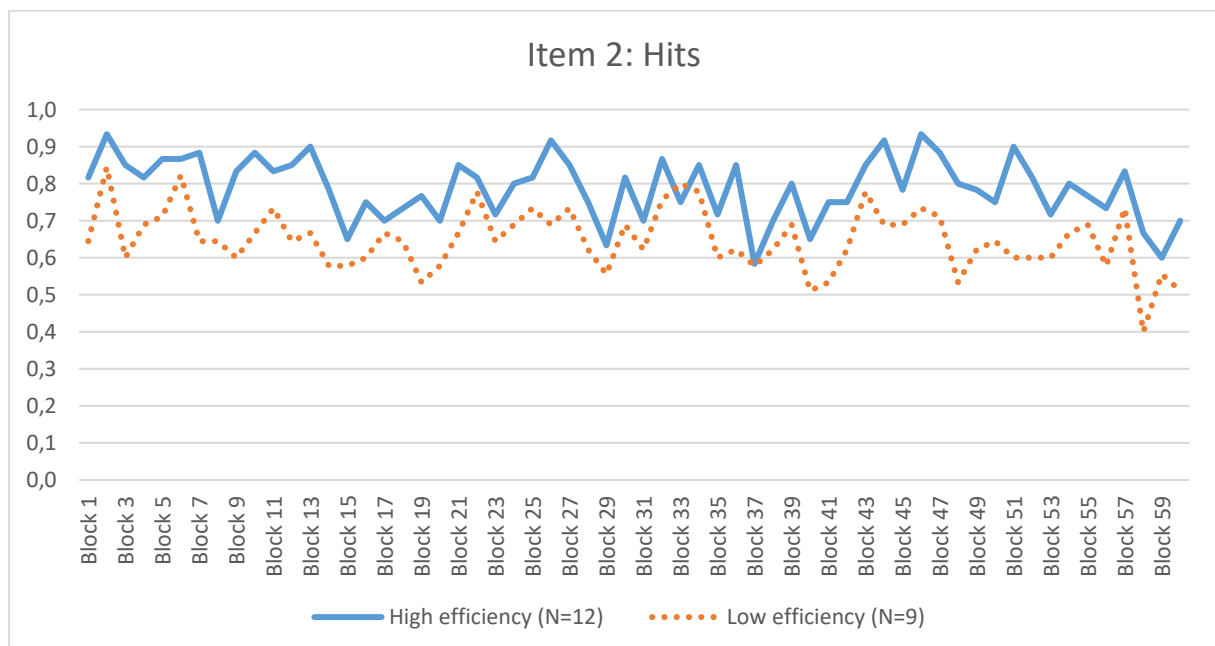
As other works on simple discrimination operant tasks already suggest, there is a minimum time to adequately respond to the proposed tasks. In this case, we have observed that in order to carry out the PERM tasks correctly, the minimum response time must exceed three seconds (a value below which no hits are observed).

Figures 4 and 5 show the graphs for item 2, finding a very similar pattern to the one observed for decision 1.

**Figure 4.** Response time for item 2 in each block of five trials, according to efficiency groups by speed of response of the participants



**Figure 5.** Hits for item 2 in each block of five trials, according to efficiency groups by response speed of the participants



Next, the participants were classified according to their hits. The High efficiency group (higher proportion of hits; N=13) and the Low efficiency group (lower proportion of hits; N=8).

The results show a classification similar to that previously carried out based on response time, in which few participants change groups, located at the limit (three participants from the high-performance group are from the group with the lowest response time, and two from the low-performing group are from the highest response time).

The data shown in the graphs confirm the results already exposed in the classification by response time: the group with the highest performance acts more slowly.

To perform the stepwise regression analysis, the variable "Mean hits" in the PERM training was used as the dependent variable, and the predictor variables were the "Response time" in the PERM, "Hits" in the spatial test EFAI-E and "Hits" in the Raven intelligence test.

Table 1 shows the correlation between the variables of interest. Taking into account the sample size, the positive and significant correlation between the hits on the PERM mental rotation task, the time it took to answer said task and the hits on the EFAI-E is notable.

**Table 1.** *Descriptive statistics and correlations between the variables analyzed.*

Variable (Mean/ <i>SD</i> ) N=21	Response		
	Time PERM	Raven	EFAI-E
Hits PERM (.74/.11)	.624**	.172	.487*
Response Time PERM (4175.92/1113.79)		.022	.174
Raven (49.28/4.59)			-.422
EFAI-E (9.85/3.1)			

\*\* $p < .01$

\* $p < .05$

Table 2 includes the data to compare the power of the three regression models according to the "stepwise" procedure to predict the mean performance of hits in the PERM task. The first model shows that the variable with the greatest predictive power on its own of the hits in the PERM is the response time to answer the trials of said training task. The second model adds the spatial task of the EFAI-E, which significantly increases the predictive power by .147 compared to the previous model. Finally, the third model adds the fluid intelligence assessed by the Raven, significantly increasing the value of  $R^2$  by .130. The Durbin-Watson value is 1.532, fulfilling the assumption of independence between the predictor variables. Finally, the tolerance values (1, .970, .812) and the variance inflation factors (1, 1.031., 1.231) show that there is no collinearity between the predictor variables.

**Table 2.** *Multiple Regression analysis models for predicting performance in the PERM task*

Model	Variable	$\beta$	$t$	$P$	$R^2$	$\Delta R^2$
1	PERM Response Time	.624	3.483	.002	.390	.390
2	PERM Response Time	.556	3.416	.003	.537	.147
	EFAI-E	.390	2.395	.028		
3	PERM Response Time	.517	3.619	.002	.667	.130
	EFAI-E	.566	3.591	.002		
	Raven	.400	2.579	.020		

*Note:* Method: Stepwise,  $p < .05$

## Discussion

The objective of this study was to test whether, in a learning task in which there were no conditions that induce fast answers, the results of other reference studies would be confirmed (Author et al., 2019, 2021; Author et al., 2008; Author et al., 2011; Author et al., 2016) in which it was observed that the time spent responding is the most relevant variable when trying to explain the differences between the participants.

The results obtained in a sample of 21 secondary school participants supported the proposed hypothesis. Participants completed 300 trials with two items per training trial (600 decisions) in a mental rotation task and could use as much time as they considered necessary to respond to each of the two training trial items. The analyzes carried out support the predictions about the role of response time in task performance. The relationship between the response time and the probability of getting it right was high and positive ( $r = .624, p < .01$ ), showing that more people get it right the longer it takes to answer. This variable is the one that obtained the greatest predictive power and explained by itself almost 40% of the variance of performance in the learning task (regression model 1;  $R^2 = .390$ ), although the general intelligence and spatial ability variables also contributed towards the prediction.

The classifications that have been made for the analysis of individual differences allow us to demonstrate that slightly more than half of the sample ( $N=12$ ) was grouped in a slower speed time and that they were the ones that obtained the most hits.

It is evident that, in previous works and now also in the present work, the time dedicated to solving the learning task is the variable that explains most of the variance in performance on the test. Thus, our results add to the evidence already provided by other recent studies (Authoret al., 2019, 2021; Author et al., 2008; Author et al., 2011; Author et al., 2016). The contribution of the present study is that it confirms the previous results under conditions of spontaneous speed, but without a trial time limit. According to De Boeck et al. (2017), most



of the literature has focused on studies with temporal restrictions to analyze the speed-accuracy trade-off, which had left the implications of the so-called "spontaneous speed" without being analyzed in depth.

The main limitation of the present study is that it has been carried out with a small sample. In order to generalize the results, it will be necessary to replicate this study in samples with a larger number of participants. Likewise, we believe that it will be interesting to also extend the number of trials. In this way, we will be able to better observe learning throughout the trials, obtaining results that complement those found in the present study. In any case, with the number of trials employed in this work, and despite the small sample value, the results are in line with those found in previous studies. The training task proposed in this study (mental rotation of images) is different from those of other studies (visual discrimination, category formation) and, furthermore, it does not have time restrictions to respond. The results confirm the relevant role of the response time shown in the aforementioned reference studies. This finding is not surprising, given the linear relationship demonstrated by Shepard and Metzler (1971) between the time it takes to process the mental rotation and the hits. The comparison process between two stimuli takes time, which will be longer the greater the rotation, and our results support this classical study.

In the present study, secondary school students did not get hits when they responded with latencies less than three seconds. About half of them responded faster and consequently had a lower performance. In the context of research on the reasons for performance differences on learning tasks, learner characteristics and task characteristics, have been studied extensively but not their interaction. Particularly, the difficulty of discrimination (e.g., Boopathiraj, & Chellamani, 2013; Pande et al., 2013), types of relationships to learn (visual, abstract, dynamic or complex, e.g., Suyatna et al., 2017) task-induced motivation (games, academic score, e.g., Kim & Kim, 2016; Wilbert et al., 2010) and training programs (e.g., Dansereau et al., 1979; Stoeger & Ziegler, 2010) have been studied. In our opinion, in future studies, it will be

necessary to study the interaction, that is, the way each person faces the task. Therefore, it will be necessary to try to answer questions such as: why do individuals not modify their behavior or, specifically, the speed at which they respond based on the success they obtain in solving the task?; On what does it depend that schoolchildren can adjust their time to respond?; Do school programs allow for response time adjustments for students who are too rushed or slow to respond?

Our results converge with others previously carried out with other spatial tasks that coincide in showing that the reflective style achieves greater performance in solving spatial tasks (Author et al, 2008; Author et al., 2011). Similarly, Author et al. (2016) showed the implications that a variable such as response time could have in managing impulsivity in people with ADHD. For all these reasons, practical implications derive from the results of this study. Thus, it would be appropriate to promote a slower and more reflective style when solving school tasks and, in particular, those with spatial components. It may be helpful for those students who solve tasks quickly but inefficiently to help them by indicating the time they have to dedicate to each task at the same time that they are taught self-regulation strategies (see Ramdass & Zimmerman, 2011). Thus, through the adaptation of the environment and the adaptation by the students themselves, the achievement of better performance results will be encouraged.

## References

- Boopathiraj, C., & Chellamani, K. (2013). Analysis of test items on difficulty level and discrimination index in the test for research in education. *International journal of social science & interdisciplinary research*, 2(2), 189-193.

- Carroll, J. B. (1993). *Human cognitive abilities: a survey of factor analytic studies*. Cambridge University Press.
- Authors (2019).
- Authors (2021).
- Dansereau, D. F., Collins, K. W., McDonald, B. A., Holly, C. D., Garland, J., Diekhoff, G., & Evans, S. H. (1979). Development and evaluation of a learning strategy training program. *Journal of Educational psychology*, 71(1), 64–73. <https://doi.org/10.1037/0022-0663.71.1.64>
- De Boeck, P., Chen, H., & Davison, M. (2017). Spontaneous and imposed speed of cognitive test responses. *British Journal of Mathematical and Statistical Psychology*, 70, 225–237. <https://doi.org/10.1111/bmsp.12094>
- DiTrapani, J., Jeon, M., De Boeck, P., & Partchev, I. (2016). Attempting to differentiate fast and slow intelligence: Using generalized item response trees to examine the role of speed on intelligence tests. *Intelligence*, 56, 82–92. <https://doi.org/10.1016/j.intell.2016.02.012>
- Hernández, J.M. (2000). La personalidad: Elementos para su estudio. Biblioteca Nueva.
- Authors (1999).
- Goldstein, D., Haldane, D., & Mitchell, C. (1990). Sex differences in visual-spatial ability: The role of performance factors. *Memory & Cognition*, 18, 546-550.
- Kagan, J., & Kogan, N. (1970). Individual variation in cognitive processes. En P. Mussen (Ed.), *Carmichael's manual of child psychology* (Vol. 1, pp. 1273–1365). Wiley.
- Kim, B., & Kim, H. (2016). Korean College EFL Learners' Task Motivation in Written Language Production. *International Education Studies*, 9(2), 42-50.

- Pande, S. S., Pande, S.R., Parate, V.R., Nikam, A.P., & Angrekar, S. (2013). Correlation between difficulty & discrimination indices of MCQs in formative exam in physiology. *South-East Asian Journal of Medical Education*, 7(1), 45-50.
- Partchev, I., & De Boeck, P. (2012). Can fast and slow intelligence be differentiated? *Intelligence*, 40, 23–32. <https://doi.org/10.18637/jss.v048.c01>
- Authors (2008).
- Authors (2011)
- Ramdass, D., & Zimmerman, B. J. (2011). Developing self-regulation skills: The important role of homework. *Journal of advanced academics*, 22(2), 194-218. doi:10.1177/1932202X1102200202
- Raven, J., Court, J. H. & Raven, J. C. (1996). *Standard Progressive Matrices*. Psychologists Press.
- Rivière, Á. (1991). Orígenes históricos de la psicología cognitiva: paradigma simbólico y procesamiento de la información. *Anuario de Psicología/The UB Journal of Psychology*, 51, 129-156.
- Authors (2016).
- Authors (2022).
- Authors (2016).
- Santamaría, P., Arribas, D., Pereña, J., & Seisdedos, N. (2005). *EFAI, Evaluación Factorial de las Aptitudes Intelectuales*. TEA.
- Shepard, R. N., & Metzler, J. (1971). Mental rotation of three-dimensional objects. *Science*, 171(3972), 701–703. <https://doi.org/10.1126/science.171.3972.701>
- Stoeger, H., & Ziegler, A. (2010). Do pupils with differing cognitive abilities benefit similarly from a self-regulated learning training program? *Gifted Education International*, 26(1), 110-123.

- Suyatna, A., Anggraini, D., Agustina, D., & Widyastuti, D. (2017, November). The role of visual representation in physics learning: dynamic versus static visualization. In *Journal of Physics: Conference Series* (Vol. 909, No. 1, p. 012048). IOP Publishing.
- Watson, J. B. (1913). Psychology as the behaviorist views it. *Psychological Review*, 20, 158-177. <https://doi.org/10.1037/h0074428>
- Wilbert, J., Grosche, M., & Gerdes, H. (2010). Effects of Evaluative Feedback on Rate of Learning and Task Motivation: An Analogue Experiment. *Learning Disabilities: A Contemporary Journal*, 8(2), 43-52.