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TRENDS/CASES

Cognitive abilities that mediate SES's effect on elementary mathematics learning: The Uruguayan tablet-based intervention

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Abstract In unequal societies the effectiveness of formal education depends on the socioeconomic status (SES) of students. Studies have shown that poverty affects the development of the brain in ways that might compromise future learning, thus increasing the differences between groups with different SES. Interest is growing in the development of tools that might change this state of affairs. This article presents a tablet-based study aimed at determining the cognitive abilities related to primary school children's math learning. The study followed the students' changes during a short intervention, the purpose of which was to improve students' performance of some of the core components of mathematical cognition; in particular, of the approximate number system (ANS), a system that supports one's ability to estimate quantities and to compare time intervals. The article presents the study's characteristics and shows how the variables that were evaluated—ANS precision, time discrimination accuracy, digit span, and mathematical achievement—depend on SES. We employ multiple regressions to show that the variance in mathematics performance attributed to SES can be explained by differences in underlying cognitive factors. The study also indicates that those students of low-SES schools who participated in more tablet activities increased their performance more than students who did fewer activities. Although the intervention's initial objective was to influence mathematical

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development and the study is not a randomized double-blind study, we argue that training the ANS can have positive effects in mathematics learning, and that this might benefit children living in low-SES contexts more than those in the general population, perhaps because of the former's initially low levels of performance in school mathematics.

Keywords Math learning · Cognitive abilities · Socio-economic status (SES) · Uruguay

Introduction

The successful acquisition of cultural abilities such as mathematics requires the development of several cognitive faculties—for example, a basic sense for numbers and spatial representations (Carey 2001; Feigenson, Dehane, and Spelke 2004). Some of these faculties are innately functional in the brain early in development (de Hevia, Izard, Coubart, Spelke, and Streri 2014). However, being present at birth (Izard, Sann, Spelke, and Streri 2009) does not mean that these faculties remain fixed for life. We can see that they indeed change by the fact that the precision and tuning of these cognitive systems improve throughout infancy and childhood (Halberda and Feigenson 2008; Halberda, Ly, Wilmer, Naiman, and Germine 2012; Odic, Libertus, Feigenson, and Halberda 2013). Appropriate training programs can also improve the precision of these abilities (DeWind and Brannon 2012; Hyde, Khanum, and Spelke 2014)—which could be implemented at schools.

One mystery of education is that not all children learn equally well. In unequal societies—that is, societies characterized by large income distribution inequalities—several factors associated with the socioeconomic status (SES) of households hinder the effectiveness of formal education (Wilkinson and Pickett 2010). For example, poverty affects the development of the brain (for review, see Lipina and Colombo 2009; Lipina and Posner 2012) in ways that might affect basic abilities needed for one to profit from traditional education programs. This, in turn, leads to a kind of Matthew effect whereby those who lag behind their peers in specific domains learn more poorly than those who already have relevant knowledge, and this increases the differences between the groups. Finding effective training programs able to enhance low-SES children's abilities is one of the main objectives of the nascent field of educational neuroscience (Sigman, Peña, Goldin, and Ribeiro 2014). One of the crucial prerequisites for any intervention is determining the cognitive faculties that are most convenient to address, in the sense of being easier to modify and most likely to have an effect. The hope of such an approach is that it can lead to cost-effective interventions that can be applied on a massive scale.

In mathematics, children from lower-SES environments typically underperform relative to children of middle- and high-SES (Sirin 2005), though, in the earliest school years, the former may be as competent as the latter with basic numerical abilities (Seo and Ginsburg 2004). Researchers still debate the reasons for these differences, but they probably include perinatal factors as well as differences in early cognitive stimulation (Lefevre et al. 2009). Thus, although early schooling could show no systematic differences in elementary numerical abilities, cognitive differences may already by present, undermining further mathematical learning (see, e.g., Libertus and Brannon 2010, for early differences in ANS performance). This raises the question of whether training in basic math cognition can help such children. In order to succeed in school mathematics, children must master a variety of abilities including those understood to be "informal mathematics abilities" (e.g., numbering and counting, comparing numbers to determine which is more or less, and calculating the answers to simple arithmetic problems using tokens or fingers) and those understood to be "formal" or "school-taught" abilities (e.g., the ability to read and write Arabic numerals, an understanding of the place-value system, and the ability to recall memorized addition, subtraction, and multiplication facts) (Ginsburg and Baroody 2003; Jordan, Kaplan, Ramineni, and Locuniak 2009; National Mathematics Advisory Panel 2008). These abilities emerge at different ages during education, and some take many years to fully master.

Before entering school, children also have a prelinguistic understanding of numbers that can be used to approximate numerical quantities, compare approximate numerical representations, and perform approximate arithmetic operations such as estimating addition and subtraction results with collections (Barth, La Mont, Lipton, and Spelke 2005; Dehaene 1992; Feigenson, Dehaene, and Spelke 2004). This understanding is based on the basic number sense—the approximate number system (ANS)—a core knowledge system (Feigenson, Dehaene, and Spelke 2004) that is present in newborns (Izard, Sann, Spelke, and Streri 2009) but changes through development (Odic et al. 2013). This system is based on a well-defined network of parietal and frontal areas that we share with other species (Nieder and Dehaene 2009) and that stays with us throughout our lives.

Although it is a core system present in all humans, some people have a less precise sense of number than others (e.g., they are worse with number estimates) (Halberda, Mazzocco, and Feigenson 2008; Mazzocco, Feigenson, and Halberda 2011). This is due to both constitutional and experiential factors, but although there is early individual variation (Libertus and Brannon 2010), the heritability of accuracy in number representation is low (Tosto et al. 2014) and this accuracy can change with appropriate training (Park and Brannon 2013). A large body of evidence has revealed that these small differences in ANS precision are related to differences in school math performance (Chen and Li 2014; Fazio, Bailey, Thompson, and Siegler 2014; Libertus 2015; Schneider et al. 2016). That is, having a more precise ANS is related to better school math performance across one's whole lifespan (Halberda, Mazzocco, and Feigenson 2008; Halberda et al. 2012). Currently, we do not know whether a game-based intervention can improve ANS precision and whether such improvement will transfer to better formal math test performance.

More importantly in this context, we do not know whether this improvement will specifically benefit low-SES children. At the same time, other cognitive abilities might need improvement in order to support mathematics learning. In particular, it has been argued that humans have a common magnitude system (Walsh 2003) that underlies our perception of time, space, and number. If this is so, besides ANS training, we might also target the training of time discrimination abilities—with the hope of transfer to mathematics, specifically in the case of low-SES children. Moreover, a large literature relates working memory capacity to mathematics-related abilities (see, e.g., Gathercole et al. 2016 and references cited therein). We did not specifically train working memory capacity, but we included a digit span task in order to control for its potential contribution.

We present the first massive, short-term intervention using the Plan Ceibal program in order to enhance mathematical learning through various complementary strategies. Plan Ceibal is the Uruguayan version of the One Laptop Per Child initiative whereby each school child receives a computer and/or tablet, and all the schools receive Internet service, in addition to the deployment of WIFI services in public places. Our project used this platform to test and train cognitive-based activities as a means of enhancing mathematics learning.

An important result in the field of cognitive-based educational interventions is that no single intervention works for all kinds of populations, and some conditions have ceiling effects that preclude any further learning with training. For instance, in one successful example of transfer from game playing to more general cognitive abilities, Goldin and coworkers have shown that they can successfully train lower-SES children's executive function and that this transfers to other tasks, but that thus far transfer only occurs for those children who attend the school less than the median attendance (Goldin et al. 2014).

It is probably the case that each cognitive ability has its own schedule, requirements, and windows of opportunity to be enhanced. It is also clear that SES impacts cognition through multiple and complex ways. After all, public health and public education measures, change of economic conditions, and economic support might alleviate SES differences when applied through a coherent program (Banerjee et al. 2015). In harmony with these factors, we propose that particular cognitive abilities might also be important targets for stimulation through gameplay—a cost-effective intervention. This requires identifying potential targets, designing effective interventions, and determining at which ages and in which groups such interventions may be maximally effective.

Our objective in the present work is to measure basic math cognitive abilities and to determine if a one-month game-based intervention can partially mediate the effects of SES on elementary formal mathematics learning. To this end, we analyze the data we obtained during a short intervention whose goal was improving formal mathematics through the stimulation of the ANS, one of the core components of mathematical knowledge (Halberda, Mazzocco, and Feigenson 2008). During the intervention we also measured other cognitive abilities (e.g., working memory span, time discrimination) and assessed formal mathematics performance. Previously, we found that both basic number discrimination (ANS) and basic time discrimination each correlate with school mathematics performance (Odic et al. 2016). Here, we tested for improvements in these abilities after intervention and compare low- and high-SES children. First we describe the tablet-based Uruguayan intervention study we ran, including the tasks relevant for this article. We describe performance in basic number discrimination, the ability to detect differences in time intervals (time discrimination, TD), digit span, and formal mathematics tests. In our analyses, we first ask whether performance in these tasks depends on SES level. Next, we attempt to disentangle the contributions made by SES from other unexplained variance sources by controlling for the measured cognitive variables. That is, we control for all the differences in formal math scores that are related to differences in cognitive variables, and we then ask a significant difference remains between high- and low-SES children. Finally, we investigate the effects of our intervention (i.e., one month of occasional tablet gameplay with games we designed to activate basic cognitive faculties like the ANS $\approx$ 2 hours of play per week). We test for improvements in both low- and high-SES children on both basic cognitive skills and formal mathematics.

Our initial objective for this intervention study was to influence mathematical development and, admittedly, the study is not a randomized double-blind study. Rather, it is instead a first-step experimental test of whether tablet gameplay can improve basic cognitive faculties like the ANS, and whether such improvements will transfer to more school-based abilities like formal math test performance. Such questions are particularly important when we consider the potential practical gains in math for low-SES versus high-SES children.

Materials and methods

Participants

A total of 454 first graders (206 girls), ages 6.42 to 8.76 (M = 7.25, SD = .46) took part in this study. Due to a variety of reasons (e.g., internet connectivity issues, failure to follow directions, lack of attention), not all children completed all tasks, so the sample base for different tasks may vary. Participating children attended 7 different schools in Montevideo. We selected the schools from different socioeconomic strata based on the Uruguayan National Public Education Administration classification (ANEP 2012); 3 schools belonged to SES quintile 1 (N = 224), and 4 schools to SES quintile 5 (N = 230). ANEP's SES school classification takes into account household education level (percentage of mothers who completed secondary education or more minus the percentage of those who completed primary education or less), socioeconomic indicators (percentage of: overcrowded households, households with access to potable water, and households with sewer problems; housing construction materials), and social integration (head of household's employment status, percentage of children living in irregular settlements, and percentage of household children attending school). After performing a factor analysis, a single factor accounts for over 65% of the variance and this is used as an index. Using this index, the ANEP team classified schools in 5 quintiles (level 1 was the lowest quintile, ANEP 2012). The SES level, thus, is a measure of the school situation, but it can be regarded as an approximation of each child's SES by the mean of the group.

Access to tablets

As part of the deployment of Plan Ceibal—the Uruguayan one-laptop-per-child initiative—before the study began, each child received an XO tablet (an Android tablet designed for younger children).

Procedure

Following a written protocol to reduce the effect of extraneous variables, we conducted assessment and training sessions in the child's classroom. Before and after approximate number system (ANS) training sessions, we assessed formal math abilities, time discrimination, digit span, and acuity in the approximate number system (ANS). We programmed all assessments and training activities as game-like tasks in JavaScript, PHP, SQL, and JQuery. Children played the games online on the 7-inch screen of their XO tablet running OS Android 4.2 (Jelly Bean). We recorded data on each child's performance in real time, over the Internet, on a secure remote server.

Study design

We visited each school two days per week for five weeks. Of the ten days, we dedicated the first and last three to evaluation of formal mathematics and cognitive abilities. During the other four days, we instigated intervention proper (see below), specifically of different ways of training the approximate number system. Overall, we report five tasks in this study: a formal math assessment task (which includes different types of subtasks; see below), an ANS acuity determination task, a time discrimination task, and a digit span task.

Formal math assessment

We assessed formal math abilities with the Prueba Uruguaya de Matemática (PUMA, or Uruguayan Math Assessment Test). PUMA evaluates different mathematical skills including number symbol knowledge, number composition and decomposition, Arabic number ordering, number line placement, and basic word problems. The first and second tasks evaluate the strategies that students use for composing and decomposing different numbers. In the first task, children have to select cards with different values (1, 5, 10, 20, 50, and 100) to compose the points awarded to a virtual character (we used target numbers 10, 8, 20, 34 and 52, 100). The second task is a reversed version of the first one: children have to select a combination of cards to match the points awarded to the virtual character (53, 50, 110, 70, 14, 36). The third task assesses understanding of the base-ten number system. We present children with a set of cards, all of them with value 10, and they have to select cards to compose the target number (targets: 100, 60, 120, 80, 40, 30). The fourth task tests number ordering. In this task, we give children a train with twenty numbered wagons, where some wagons' numbers are missing, and the children have to drag the missing numbers—presented in a scrambled order at the bottom of the screen—back to the wagons in the right order (missing values: 5, 8, 10, 12, 15, 18, 20). The fifth task tests counting and cardinality. We show children a number of dots, which they have to count; subsequently, they have to drag the virtual characters to the corresponding square on a game board (targets: 16, 12, 20, 9). The sixth task measures knowledge of number ordering. We give children cards displaying numbers 1 to 10 in a scrambled order, and ask them to place the cards in decreasing order on the top of the screen. The seventh task assesses the mental number line. The screen presents an empty number line with a single anchor number (5, 7, 6, 3, 5, or 8) and the children have to drag two numbers (4 and 9, 1 and 9, 4 and 10, 5 and 9, 1 and 7, or 1 and 6) to the correct position on the line given the anchor. The eighth PUMA task tests basic word problems. Children see different toys with price tags on the tablet screen and have to answer different simple problems; e.g., "Select two toys totaling $90".

Since the number of trials for each task within PUMA was insufficient for individual analysis, we computed a single score combining the percentage of correct answers across all different tasks. The children performed the PUMA tasks over two days in pretest and two days in post-test (the first day, tasks 1–4; the second day, tasks 5–8). Overall the PUMA tasks take less than 10 minutes each day; each trial had an upper duration of one minute, after which the program presented another trial.

Time discrimination

In this game, two monsters appear on the tablet screen. On each trial, each monster produces a noise for a certain amount of time. Children select the monster who sings the longest by tapping them on the screen. Time ratios (1.20, 1.25, 1.50, 1.60, 2.00, 2.40, 2.50, 3.0) are presented in random order. The longest time interval used was three seconds, whereas the shortest was one second. On half of the trials, the left monster starts to sing first; and, similarly, on half of the trials, the left monster sings longer. We computed the percentage of correct answers.

Digit span

We use the digit span test to measure attention and working memory. We present an increasing number of digits—between 1 and 6—visually on the screen, and after a brief pause, they disappear. Children have to type the sequence on a number pad on the screen.

ANS acuity

We assessed precision of the approximate number system using the standardized Panamath task (Halberda and Ly 2015). We showed children two sets of dots of two different colors, for a brief period of time so as to prevent counting. To reduce inferences made from the continuous properties (e.g., cumulative dots area), half of the trials had cumulative areas congruent with the number of dots, and half had incongruent. By tapping on the tablet screen, children had to choose which side of the screen had more dots.

ANS training task

On days four through eight, children completed four ANS training sessions, with a duration of six minutes each. ANS training, based on Panamath, included the possibility of delivering feedback. The first three trials in each session were very easy and served as a practice. During the training task, children were given a positive "ding!" sound for correct or an "err!" sound for incorrect answers, as feedback. In the second and fourth days of training, we introduced two variants of training. In one case, children got the easier tasks first and the harder tasks later (easy to hard); whereas, in another case, children got the harder tasks first and the easier ones later (hard to easy). Easy tasks refer to ratios of 1:3 dots and hard tasks to ratios of 6:7 dots. Although some have reported that the easy-to-hard presentation leads to better learning in ANS (Odic, Hock, and Halberda 2014), we did not find a significant difference in this study. Our analysis does not report these different training protocols; we just report the amount of training.

Results

In Figure 1, we show the dependence with SES of the cognitive variables we evaluated. As one can see, during baseline evaluations (in red), children from high SES (5) are performing better than children from low SES (1). Another aspect apparent in the results is that, after the intervention (in blue), all children improved, and perhaps the differences between SES may not be as large after the intervention (blue) than before (red) (but see, below).

We subjected the results of the four tasks to a mixed-effects ANOVA using SES level and evaluation (baseline or postintervention) as fixed effects and subject as random effect. In all cases we found significant effects of SES (PANAMATH: $p<0.001$; TD: $p<0.001$; DS: $p<0.01$; PUMA: $p<0.001$) and in all but digit span we found differences between the pre- and the post-test (PANAMATH: $p<.001$; TD: $p<0.001$; DS $p<0.01$; PUMA: $p<0.001$). None of the interactions was significant ($p>0.1$ in all cases). Although in Figure 1 there is a tendency toward a reduction of differences in PUMA scores between different SES levels from baseline to postintervention, the fact that no significant interactions exist indicates that the effect—if present—is not big enough to counter the variance. Also, there is a moderate level of attrition. A mean of 147.5 subjects from SES 1 and 127.25 from SES 5 completed the tasks at pretest and 123.75 and 114.5 at post-test (the non-integer mean number is due to the fact that not all children completed all tasks each day). A two-way ANOVA comparing the number of children with SES level and day as the two factors shows a main effect of day on number of children ($F(1,12)=5.46$, $p=0.03$) and a marginal effect of SES ($F=3.97$, $p=0.0694$), but no interaction ($F=0.58$, $p=0.46$). Therefore, there were no significant differences in attrition between SES levels.

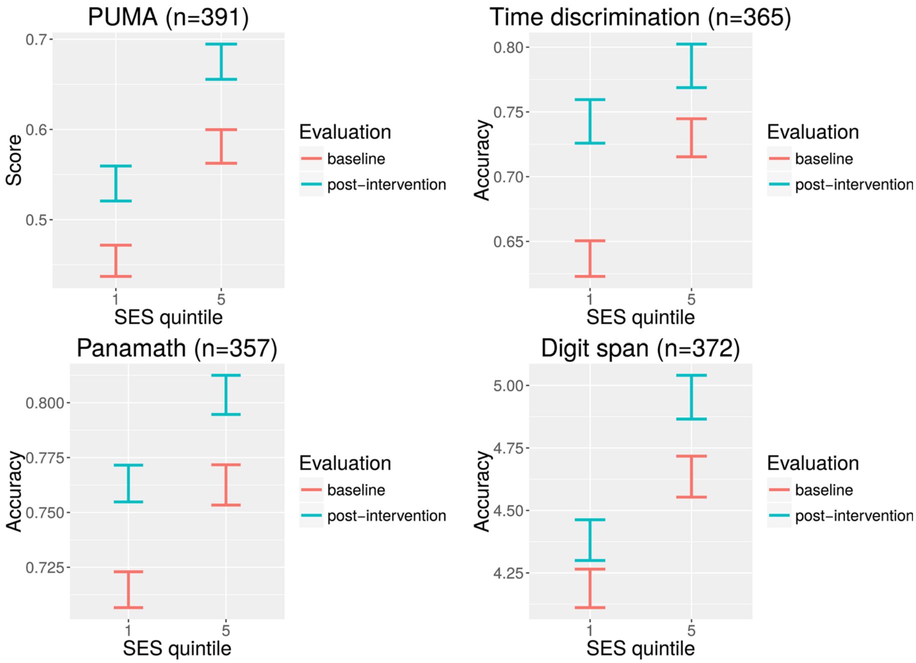

Figure 1 Formal mathematics test and cognitive abilities as functions of school SES level (1–5), in the baseline (*red*) and postintervention visits (*blue*)
Note: Upper-left graph shows PUMA accuracy, which is how we measure formal mathematical ability. The other graphs display cognitive variables: approximate number system (ANS), the capacity to discriminate two time intervals (time discrimination, TD), and digit span (DS). All the variables show significant variations with SES (see the text for details). Error bars correspond to ±1 standard errors. (Color figure online)

As a final check, we note that the results of Figure 1 include children who had different levels of exposure to the intervention and aggregate data from children who participated in all or only a part of the evaluation. We found that the evaluation of within-subject data gives the same results (not shown).

Analyzing the effect of SES

What we have shown above is that formal mathematical achievement depends on SES level of the school, and that there is also a relationship between cognitive variables and SES. Considering the improvements we observed following the intervention, because all of the graphs in Figure 1 show a similar pattern, it might be the case that what changed during the intervention is a single (or a few) factors. Alternatively, the changes in Figure 1 might each rely on an independent mechanism. We consider here whether common factors can explain these relationships or whether, instead, they are based on independent ones.

In previous work (Odic et al. 2016), we found correlations between formal math performance and cognitive variables such as ANS and time discrimination that were partially independent of each other. To evaluate whether ANS or time discrimination capabilities mediate the effect of SES, we performed a series of multiple regressions between formal mathematics scores, using SES and each cognitive factor as predictors in the pretest evaluation. We show these regression results in Table 1 and illustrate them in Figure 2.

Both Table 1 and Figure 2 show that, with the exception of SES, all cognitive predictors contribute independently to differences in PUMA scores. Due to sample sizes, we cannot perform a regression having all three cognitive factors and SES as predictor variables. Nevertheless, we can pool baseline and postintervention scores and do such a regression

Table 1 Regression coefficients and significance for the cognitive and SES contributions to symbolic mathematics

Outcome variable	Predictor variable	β	Standard error	Significance	Adj. R2	N
PUMA	SES	0.52	0.15	<.001***	0.06	177
PUMA	SES	0.46	0.14	<.01**	0.08	177
	ANS accuracy	0.16	0.07	<.026*		
PUMA	SES	0.40	0.12	<.01**	0.17	214
	Time discrimination accuracy	0.34	0.06	<.001***		
PUMA	SES	0.25	0.12	0.04*	0.23	211
	Digit span	0.44	0.06	<.001***		

Note: In all regressions, coefficients for cognitive variables and SES were significantly different from 0.
*$p < 0.05$
**$p < 0.01$
***$p < 0.001$

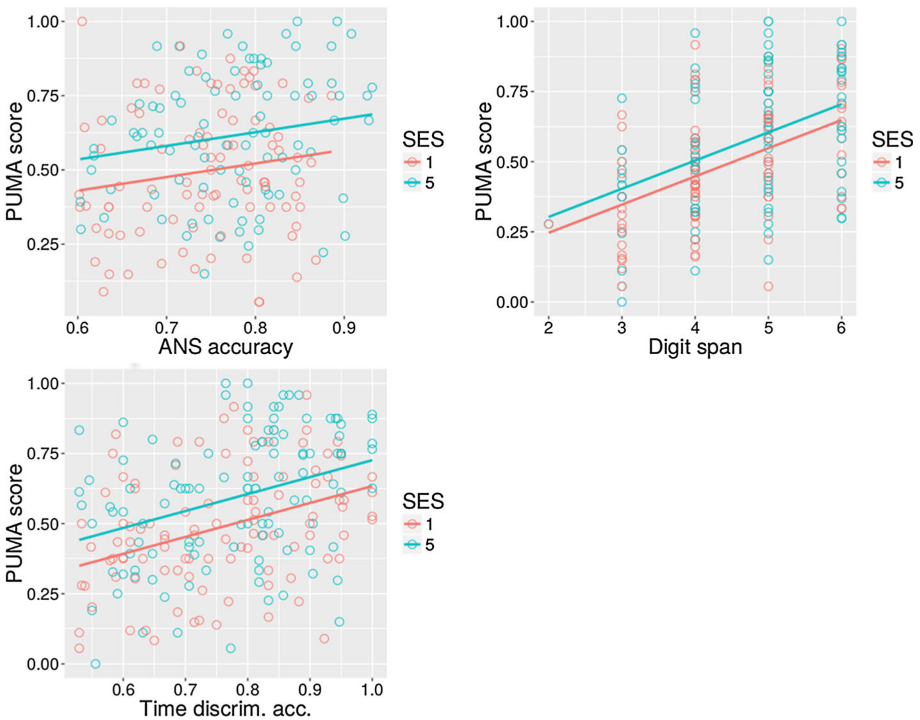

Figure 2 Relationship between formal math performance (PUMA scores) and cognitive variables (ANS, *upper left*; TD, *bottom left*; digit span, *upper right*), and SES
Note: Lines show regression model predictions.

analysis. What the analysis shows is that, combined, these factors account for over 30% of the variance, and that they all contribute except SES.

To do the regression in Table 2, we created a variable called "Evaluation", which takes values 0 (pretest) and 1 (post-test). The first 2 rows correspond to a regression of PUMA, with SES and Evaluation as independent variables. The other 5 rows correspond to another regression containing all cognitive variables as well as SES and Evaluation. In both models, we included a subject random effect.

According to our hypothesis, SES produces its effects on formal mathematics through its effect on cognitive variables. We do not expect this relationship to vary from one SES to another, hence we do not expect any interaction. We nevertheless compared models with and without interaction terms and found no significant improvement in model fit to data (Fs between 0.42 and 3.56, p-values between 0.51 and 0.06).

Dose-dependent effect and the effectiveness of the intervention

As we mentioned before, the characteristics of the intervention impeded the proper application of control groups, so it is not possible to arrive at causal conclusions using the present study. Nevertheless, we can obtain a hint by comparing the results in the PUMA test with the number of instances a child played the training games during the intervention. Given that not all children performed all the games (for technical reasons like malfunctioning tablets or lack of Internet connection), there is a natural variance that we can take into account in order to do so.

In Figure 3, we indicate the moderate increase in PUMA scores of those children who played more intervention games. Crucially, this increase is more pronounced in low-SES children than high-SES children. The graph of Figure 3 shows post-test scores. To evaluate the separate contributions of pretest scores and training sessions, we performed a new regression analysis (Table 3). The main result of this analysis is that, besides pretest scores,

Table 2 Multiple regression including a variable to reflect pre- and post-tests (evaluation), SES, and all three cognitive factors

Outcome variable	Predictor variable	β	Standard error	Significance	Log likelihood	N
PUMA	SES	0.31	0.16	0.05	−278.6	173
	Evaluation	0.49	0.14	<.001***		
PUMA	SES	0.14	0.14	0.29	−208.4	173
	Evaluation	0.35	0.10	<.01**		
	ANS accuracy	0.19	0.06	<.01**		
	Time discrimination	0.05	0.06	0.43		
	Digit span	0.35	0.10	<.001***		

Note: To do the regression, we created a variable called 'Evaluation' that takes values 0 (pre-test) and 1 (post-test). The two first rows correspond to a regression of PUMA with SES and Evaluation as independent variables. The other five rows correspond to another regression containing all cognitive variables as well as SES and Evaluation. In both models, a subject random effect was included.

*$p < 0.05$

**$p < 0.01$

***$p < 0.001$

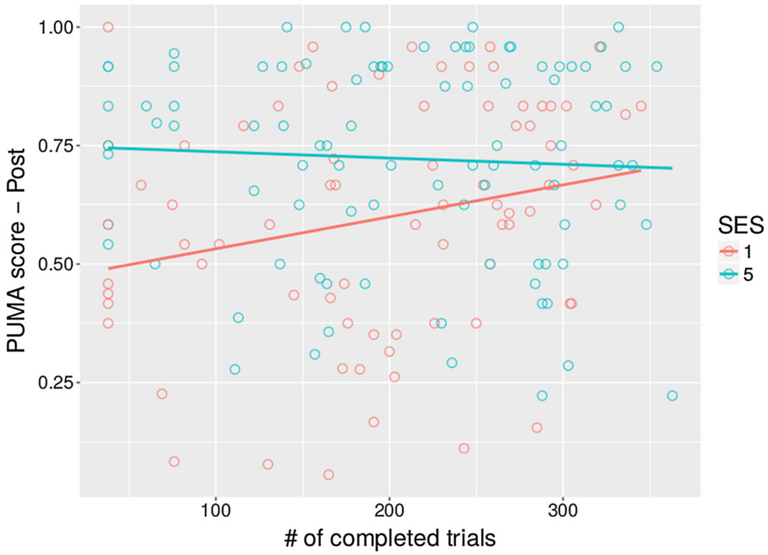

Figure 3 Effect of the number of completed Panamath trials on symbolic math scores postintervention, showing a stronger relationship for the lowest SES level
Note: PUMA, SES: $p < .001$; number of trials: $p < .01$; interaction: $p < .01$.

Table 3 Regression coefficients for the effect on PUMA post-test scores (PUMA-post) of pretest PUMA scores (PUMA-pre), SES, and the number of completed Panamath trials (# of trials), as well as their interactions

Outcome variable	Predictor variable	β	Standard error	Significance	Adj. R2	N
PUMA-post	PUMA-pre	0.72	0.05	<.001***	0.56	167
	SES	0.12	0.10	0.24		
	# of trials	0.14	0.08	.06		
	SES x # of trials	−0.21	0.10	.04*		

Note: The coefficient for the number of completed trials represents the dependency (slope) of PUMA scores on this variable for SES 1. The interaction coefficient is the difference of slopes for SES 1 and 5.

*$p < 0.05$

**$p < 0.01$

***$p < 0.001$

doing more trials of the intervention games leads to an increase of the PUMA score in the post-test, especially for low-SES children.

Discussion

How does SES impact mathematics learning? One possibility is that school performance itself is affected, separate from cognitive skills. Another possibility is that SES first affects basic cognitive abilities, and then these abilities help or hinder school learning for each child. Here we found striking support for this later account. First, we found a strong relationship between SES and formal math performance (PUMA). Second, when we combined performance across the baseline and postintervention measures, we found that it was cognitive abilities, rather than SES, that significantly predicted formal math performance (Table 2). And, we found the suggestion of an effect whereby our intervention to improve cognitive abilities (i.e., number of intervention games played) related to amount of improvements in formal math performance (PUMA), especially in low-SES children (Figure 3; Table 3). These results suggest a possible causal mechanism by which low SES affects basic cognitive abilities in mathematics (e.g., ANS, TD) and these abilities then affect school math performance. It also suggests that intervening to improve these basic abilities may lead to improved math performance. However, we must be cautious. Because this was not a randomized double-blind study, these conclusions can only be suggestions to inspire more research and cannot be definitive.

This work presents our first efforts to apply known concepts from cognitive science to generate evidence-based educational interventions. We based our intervention on a set of games and activities that can be played on many electronic devices, such as telephones, computers, or tablets. We have previously shown that during the intervention the performance on symbolic mathematics increases (Valle Lisboa et al. 2016). Here, we emphasize that those students who participated in our study come from different socioeconomic statuses (SES), which has been an important factor in discussions of differences in mathematics learning. Let us make clear that, due to organizational restrictions, we could not conduct a controlled-experiment, so our conclusions are partial—but, together with our previous analyses (Valle Lisboa et al. 2016), the evidence we present here points to the usefulness of this kind of intervention. In all measures of symbolic mathematics, the performance post-intervention was better than baseline. Moreover, previous analysis of the sample shows that students who participated in the intervention but were evaluated only once do not differ from those who took the two tests (pre- and post-), suggesting that this increase is not due to test repetition (Valle Lisboa et al. 2016). Of course, because we did not directly manipulate such variables, it might be the case that class assistance rather than our intervention is the main factor explaining performance increases. Although we cannot rule out this interpretation completely, there is some indication that there is an increase in performance attributable to the intervention.

After training ANS, we expected PUMA differences between different SES children to be reduced, in line with results showing that these types of interventions are more effective with low-SES populations (e.g., Goldin et al. 2014). Figure 3 shows that low-SES children's performance increases more when they take part in more intervention trials. This contrasts with results showing no interactions between SES and pretest versus post-test PUMA scores (Figure 1 and the text below)—meaning, in essence, that both SES scores change the same amount.

We believe that this discrepancy has two main explanations. In the first place, we might, in fact, have not reached a saturation point in learning after our short intervention. The intervention appears to be helping both the low- and high-SES children, and perhaps with more training time these children would attain more similar levels of performance. The other explanation is that the study has a lot of variability, and so a weak interaction might have been lost in the variance. Moreover, the concurrence of extraneous factors (like school assistance) can hide the effect of the intervention. An hypothesis able to explain these somewhat contradictory results is that there is, indeed, a differential effect on both populations (Figure 3; Table 3), but that other factors (e.g., schooling) are also present, making the interaction more vulnerable to noise (see Figure 1).

More generally, our results are in line with a group of studies showing that training the ANS can have beneficial effects in mathematics learning (DeWind and Brannon 2012; Hyde, Khanum, and Spelke 2014). The picture that emerges from our study is, thus, that low-SES children have less access to stimulation of the underlying core systems responsible for math learning; and that training these systems, even during a few sessions, can have a positive impact on math learning. If this is so, we can cut the vicious circle that in unequal societies make children less permeable to education, a fact that enhances inequality. What is encouraging is that, taken together with previous works (DeWind and Brannon 2012; Goldin et al. 2014; Hyde, Khanum, and Spelke 2014; Kirkland, Manning, Osaki, and Hicks 2015), our results indicate that this type of training, mediated by accessible devices, could be the basis of a powerful strategy to design an effective policy that favors equality.

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