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The Cognitive Estimation Task Is Nonunitary: Evidence for Multiple Magnitude Representation Mechanisms Among Normative and ADHD College Students

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Abstract

There is a current debate on whether the cognitive system has a shared representation for all magnitudes or whether there are unique representations. To investigate this question, we used the Biber cognitive estimation task. In this task, participants were asked to provide estimates for questions such as, "How many sticks of spaghetti are in a package?" The task uses different estimation categories (e.g., time, numerical quantity, distance, and weight) to look at real-life magnitude representations. Experiment 1 assessed (N = 95) a Hebrew version of the Biber Cognitive Estimation Task and found that different estimation categories had different relations, for example, weight, time, and distance shared variance, but numerical estimation did not. We suggest that numerical estimation does not require the use of measurement in units, hence, it represents a more "pure" numerical estimation. Experiment 2 found that different factors explain individual abilities in different estimation categories. For example, numerical estimation was predicted by preverbal innate quantity understanding (approximate number sense) and working memory, whereas time estimations were supported by IQ. These results demonstrate that cognitive estimation is not a unified construct.

Keywords: numerical estimation, magnitudes, approximate number sense, executive function, cognitive estimation task

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Numerical estimation is a process that is crucial to everyday life. For example, it is necessary for estimating the amount of change one would receive after making a purchase, estimating the weight of luggage prior to taking a flight, or evaluating the amount of time it would take to complete an essay. A few processes are required to provide a reasonable estimate for a cognitive estimation question such as, "How long it will take to finish an essay?" First, you must activate your set of semantic memories (what is the expected length of the essay?); next, you must plan your future step (I should answer approximately two questions a day to complete the project on time); then you must activate your working memory (WM) and sustain attention to complete the task (Bullard et al., 2004).

Cognitive estimation is the ability to give logical answers to questions for which a specific exact answer is not available; however, to give approximate logical answers, semantic knowledge is necessary (Shallice & Evans, 1978). In this paper, we administer cognitive estimation questions across three experiments to investigate cognitive representations for different types of quantities (e.g., numerical, time, distance, and weight) and to assess evidence for a unified or distinct magnitude representation mechanism.

The Role of Executive Function in Cognitive Estimation

The cognitive estimation task was originally designed to test executive function (EF; Shallice & Evans, 1978). EF is an umbrella term for control processes that modulate the operation of cognitive subprocesses including WM, attention, inhibition, self-monitoring, and self-control. It is well known that EF develops during childhood (Zelazo et al., 2003), and, indeed, Harel, Cillessen, Fein, Bullard, and Aviv (2007) found that cognitive estimation abilities improve systematically in normally developing children, with a sharp rise in performance between the ages of 5 to 9 years, and a flatter increase from 9 to 16 years.

Although there is a general agreement that the cognitive estimation task requires EF and semantic memory (Wagner, MacPherson, Parente, & Trentini, 2011), the role of numerical estimation in cognitive estimation tasks is still largely unknown. We aimed to fill this gap by examining magnitude representations and the role of numerical estimation in a cognitive estimation task. Specifically, this study examined the role of EF (e.g., planning, attention, WM), IQ, and innate magnitude representation abilities (related to numerical estimation) in a cognitive estimation task.

From Innate Quantity Representation to Exact Calculations and Estimations

Mental arithmetic is a relatively new cultural invention. However, converging evidence from infants, preschool children, adults, and even nonhuman primates suggests that the representation of approximate quantities – also referred to as the approximate number system (ANS) – is a foundational ability. It was found that the ANS is supported by the intraparietal sulcus (IPS) in the posterior parietal cortex (PPC; Ashkenazi, Rosenberg-Lee, Tenison, & Menon, 2012; Cantlon, Brannon, Carter, & Pelphrey, 2006; Cantlon et al., 2009; Cohen Kadosh, Lammertyn, & Izard, 2008). The ANS is the preverbal ability to understand approximate quantity and the relation between quantities (e.g., what is approximately larger, 5 units or 10 units?); the approximate number of items in visual or auditory arrays can be represented without verbally counting. The ANS is believed to be the foundation of school arithmetical processing, and positive connections can be found between individual abilities in school arithmetical processing and the acuity of ANS representation (Halberda, Mazzocco, & Feigenson, 2008).

The ANS is commonly investigated using a nonsymbolic comparison task in which a participant is presented with two different-colored arrays of dots and is asked to identify which array has more dots (Halberda & Feigenson, 2008; Halberda, Ly, Wilmer, Naiman, & Germine, 2012; Halberda et al., 2008). However, except for dot representations of nonsymbolic quantities, there is a current debate on whether the human brain possesses a shared (ANS based) or distinct representation of various magnitudes, such as weight, distance/length, and time (Cohen Kadosh et al., 2008). A theory of magnitude (ATOM; Walsh, 2003) proposes a common mechanism for the processing of all quantities (Gallistel & Gelman, 2000) such as time, space, and numerals (Walsh, 2003). Based on the ANS view, this common mechanism develops from a single magnitude system operating from birth (Cohen Kadosh et al., 2005; Fias, Lammertyn, Reynvoet, Dupont, & Orban, 2003; Kaufmann et al., 2005; Shuman & Kanwisher, 2004). Indeed, evidence for a single, common magnitude representation mechanism can be found as early as infancy. A six-month-old infant can detect changes in time (VanMarle & Wynn, 2006) and quantity (Xu & Spelke, 2000) in the ratio of 1:2, but will fail at detecting a change for a ratio of 2:3. Detectable ratios improve with age, and by the age of 10 months, an infant can detect changes in quantity and time by a ratio of 2:3 (Brannon, Suanda, & Libertus, 2007).

It is well known that attention-deficit/hyperactivity disorder (ADHD) – usually diagnosed in childhood – is characterized by deficits in attention and EF and often by arithmetical deficits (Simon, Czobor, Balint, Meszaros, & Bitter, 2009; Willcutt, Doyle, Nigg, Faraone, & Pennington, 2005). Hence, the next section will discuss deficits in arithmetical abilities among individuals diagnosed with ADHD.

Arithmetical and Numerical Abilities Among ADHD Participants

ADHD is a frequently diagnosed neurodevelopmental disorder (population rate is between 10% of school-age children (Faraone, Sergeant, Gillberg, & Biederman, 2003) and around 2.9% in adults (Faraone & Biederman, 2005) that is characterized by EF deficits in planning, WM, response inhibition, and sustained attention (Simon et al., 2009; Willcutt et al., 2005). Further, ADHD is associated with learning disabilities (Czamara et al., 2013) such as dyscalculia, which is a math learning disability characterized by deficits in the acquisition of numerical abilities and calculation skills. These deficits cannot be due to low IQ, inadequate schooling, or sensory impairments (von Aster & Shalev, 2007). A recent study indicated that children who have moderate and high symptoms of ADHD have a 50% greater chance of being diagnosed with dyscalculia than children with no symptoms of ADHD (Czamara et al., 2013). Even in children with ADHD who are not diagnosed as having dyscalculia, some arithmetical difficulties often found. Specifically, a common view indicates that students with ADHD show a deficit in complex arithmetic and arithmetical verbal problems because of the involvement of EF – especially inhibition – needed to solve these problems (Laasonen, Lehtinen, Leppamaki, Tani, & Hokkanen, 2010; Passolunghi, Marzocchi, & Fiorillo, 2005). Moreover, Kaufmann and Nuerk (2008) discovered significant differences in basic number comparison skills that favored control participants over ADHD participants. Finally, it has been suggested that a temporal processing weakness (the nonverbal ability to perceive and represent time) is one of the hallmarks of ADHD (Castellanos & Tannock, 2002; Toplak, Dockstader, & Tannock, 2006). Thus, when a group of ADHD participants were asked to verbally approximate a duration of time, they gave extreme approximations for cognitive estimation questions in the time category (Hurks & Hendriksen, 2010). Few studies have tested an ADHD sample with the cognitive estimation task. Thus, a secondary aim of the present study was to examine cognitive estimation across categories (e.g., time, quantity, and weight) in participants that had been diagnosed with ADHD. We predicted that cognitive estimation would be related to arithmetical and numerical abilities.

The Aims of the Current Experiments

The primary goal of the present research was to examine the cognitive representations of different types of quantities (e.g., numerical, time and weight) using cognitive estimations of different magnitudes. Bullard and colleagues (2004) suggest using a standardized version of the Biber Cognitive Estimation Task (BCET), which is composed of four different categories: numerical quantity, weight, distance/length, and time/age. In the BCET, participants provide cognitive estimations for different categories, and thus, it functions as an innovative way to investigate numerical quantity representations. According to ATOM, all of the categories will be based on a unitary magnitude representation mechanism. Yet, according to the structure of the BCET, four different representation mechanisms should be found. Hence, we expected to find evidence for a few magnitude representation mechanisms.

Moreover, previous studies have suggested that cognitive estimation is not a unitary task and is instead supported by (a) numerical estimation, (b) EF, and (c) IQ. Thus, another goal of the present study was to test the relation between different categories of the BCET and domain specific abilities (e.g., ANS) or domain general abilities (e.g., EF, attention, and IQ). We hypothesized that the ANS would have stronger and more meaningful correlations with quantity estimation compared to other estimations. On the other hand, domain general abilities (such as EF) would have stronger and more meaningful correlations with non-numerical estimations such as time and weight.

A secondary objective of the present study was to test cognitive estimation abilities in ADHD participants. ADHD populations have been characterized by weakness in sustained attention, EF, and WM. Accordingly, we predicted that ADHD participants would (a) show extreme responses in all the cognitive estimation categories and (b) show a particular weaknesses in time estimation (Hurks & Hendriksen, 2010). Hence, we expected to see very extreme responses for the time estimation questions.

The present study involved three experiments. The first experiment aimed to create Hebrew norms for the BCET. To do so, we presented a modified Hebrew version of the BCET to a normative sample of 95 participants (*M* = 31.08 years; *SD* = 8.37). We tested the Hebrew version of the BCET and examined the influences of the estimations.

The second experiment aimed to deepen our understanding of cognitive magnitude representational mechanisms of different magnitudes by examining the relations between cognitive magnitude representational mechanisms and general cognitive abilities such as an innate approximate representation (e.g., ANS) or EF. The second experiment tested these relations in a group of typically developed college students and a group of students diagnosed with ADHD.

The BCET is a short questionnaire with only five questions in each estimation category. For the third experiment, we created a new cognitive estimation task in Hebrew with three different categories. Every category included 14 questions, in an attempt to increase statistical power. Hence, in Experiment 3, in an extended version of the BCET, we aimed to compare the estimation abilities of typically developed college students and a group of students who had been diagnosed with ADHD.

Experiment 1: Creating Hebrew Norms for the BCET

Method

Participants

All participants were volunteers, some of whom were university students, and others were adults recruited via email and Facebook (these participants complete the task online using Googledocs). Each participant signed an informed consent form and was asked to complete the questionnaires described below. From our sample, which included 114 participants, 75 participants completed an online version of the questionnaire and 39 completed the “paper and pencil” version of the questionnaire. We started with a background questionnaire. Eighteen participants were eliminated for the following reasons: one for having a history of regular drug or medication use (e.g., antidepressants), six due to a history of psychiatric conditions (e.g., bipolar disorder), two due to head trauma requiring medical treatment, one because of evidence of a neurological disorder (e.g., epilepsy), and eight because of a learning disability diagnosis (e.g., a reading disability). After these exclusions, 95 participants remained (64 were female). The average age was 31.08 years (*SD* = 8.37), and the number of years of education was 16.032 (*SD* = 2.49). The study was approved by the local Ethics Committee of the School of Education at the university. Written consent was obtained according to the Helsinki Declaration.

Procedure

Three measures were administered: (a) a background questionnaire, containing educational, demographic, and medical information; (b) a set of 20 estimation questions, to which participants responded in unspecified units (e.g., responding to time estimation question in hours, minutes, or seconds) for the answer, and when scoring the protocols, the experimenter converted each answer to the units provided in Table 1 (e.g., hours); (c) self-reported school abilities, assessed by questionnaire. Participants had to answer the question (on a scale from 1 to 10, compared to 10 of their peers), “I am better in math/writing/science than how many of my peers?”

Results

Descriptive Statistics

Table 1 reports descriptive statistics including the item number, category, units of measurement, mean, standard deviation, minimum, maximum, and percentile ranges. Most of the questions were directly translated from English to Hebrew. However, some were customized to fit Israeli culture. For example, we changed the question “How many slices of bread are there in a one pound loaf?” to “How many slices of bread are there in a 750 gram loaf?” to fit relevant measurement units. Additionally, we changed the question “How many potato chips are there in a small, one ounce bag?” to a question asking about a snack (called Bamba) that is more popular in Israel: “How many pieces of Bamba are there in a small bag?”

Table 1

Item Statistics for the Development Sample

Item	Category	Units	Minimum	Maximum	*M*	*SD*	5th	95th
1	Quantity	Seeds	12.00	1000.00	171.14	195.52	20.00	517.50
2	Weight	Grams	0.80	2500.00	214.97	281.47	20.00	540.00
3	Quantity	Sticks	25.00	1000.00	170.06	156.74	40.00	500.00
4	Distance/length	Kilometers	0.40	60.00	12.39	11.11	1.00	35.20
5	Distance/length	Meters	0.30	25.00	3.03	3.09	0.78	10.00
6	Time/age	Months	0.25	83.33	11.70	12.95	1.00	36.00
7	Weight	Kilometers	0.20	10.00	2.39	1.36	1.00	5.00
8	Distance/length	Kilometers	0.00	200.00	13.7	21.72	1.38	32.50
9	Quantity	Brushings	20.00	1000.00	140.79	154.07	26.30	470.00
10	Quantity	Bambas	15.00	275.00	48.26	38.95	20.00	100.00
11	Time/age	Minutes	1.00	180.00	15.81	20.67	3.00	44.00
12	Time/age	Years	80.00	124.00	108.94	7.70	99.50	121.25
13	Distance/length	Centimeters	1.00	60.00	12.29	6.41	5.00	20.00
14	Weight	Kilos	0.07	10.00	2.16	1.71	0.47	6.00
15	Time/age	Minutes	0.17	60.00	8.97	8.04	1.00	20.00
16	Distance/length	Meters	0.01	7.00	2.58	1.363	0.90	5.20
17	Quantity	Slices	10.00	70.00	23.10	9.86	12.00	40.00
18	Weight	Grams	16.00	8000.00	1244.11	1227.84	80.00	3250.00
19	Weight	Kilos	120.00	500.00	217.54	60.70	148.00	325.20
20	Time/age	Days	2.00	30.00	12.226	6.37	3.00	22.40

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Cronbach's alpha (α)

We calculated Cronbach's alpha (α) for all estimation categories. In the numerical quantity category, Cronbach's alpha = .38. Excluding only one question improved the Cronbach's alpha to .43. In the weight category, Cronbach's alpha = .54. Excluding only one question improved the Cronbach's alpha to .66. In the distance category, Cronbach's alpha = -.2. Excluding every one of the questions resulted in negative Cronbach's alpha, indicating that the item's covariance was extremely poor. In the time category, Cronbach's alpha = .16. Excluding the two questions improved the Cronbach's alpha to .25.

Structural Equation Modeling (SEM)

We created a theoretical model to test the multivariate relations between multiple background variables and learning abilities and estimations, and to test this model we used SEM. We also used bootstrap estimation 5000 times to test significance, due to the small sample size. The first model is presented in Figure 1. The result indicated that gender (β = -0.54, $p < .05$, bootstrap $p < .05$), education (β = -0.51, $p < .05$, bootstrap $p < .05$) and math level (β = 0.78, $p < .05$, bootstrap $p < .05$) predicted estimation performance. Age, form of answering, and writing and science levels did not (minimum $p = .45$, bootstrap minimum $p = .47$). However, the model fit was poor ($\chi^2/df = 1.87$, $p < .001$; CFI = .75; RMSEA = 0.09), and according to the Bollen-Stine bootstrap, $p = .024$, the model was not correct. Therefore, we changed the model to better fit the data according to the modification indices of the AMOS program. First, we added a bidirectional connection between education and age. Second, we added a bidirectional connection between the errors for time/duration and distance/length and between time/duration and weight. Third, we trimmed nonsignificant connections. Fourth, we added a bidirectional connection between math level and form of answering. Fifth, we added a bidirectional connection between math level and education.

As in the previous model, the results indicated that gender (β = -0.55, $p < .05$, bootstrap $p < .05$), education (β = -0.63, $p < .05$, bootstrap $p < .05$) and math level (β = 0.73, $p < .05$, bootstrap $p < .05$) predicted the variance in estimation performance. Specifically, males gave more extreme estimations than females, participants with higher math abilities (according to self-reports) gave more extreme estimations than participants with low math abilities, and participants with higher education levels gave less extreme estimations than participants with lower education levels.

Form of answering, however, did not predict variance in estimation performance ($p = .84$). The bidirectional connection between the errors for time/duration and distance/length (β = -0.24, $p < .05$, bootstrap $p < .05$) and time/duration and weight (β = 0.21, $p < .05$, bootstrap $p < .05$) both reached significance (see Figure 2; all the values are standardized). All of the categories were significantly predicted by the latent variable cognitive estimation task (CET): time/duration (β = -0.24, $p < .05$, bootstrap $p < .05$), numerical quantity (β = -0.24, $p < .05$, bootstrap $p < .05$), distance/length (β = -0.24, $p < .05$, bootstrap $p < .05$), and weight (β = -0.24, $p < .05$, bootstrap $p < .05$). The model fit was good ($\chi^2/df = 1.23$, $p = .24$; CFI = .95; RMSEA =.05), and according to the Bollen-Stine bootstrap, $p = .26$, the model was correct.

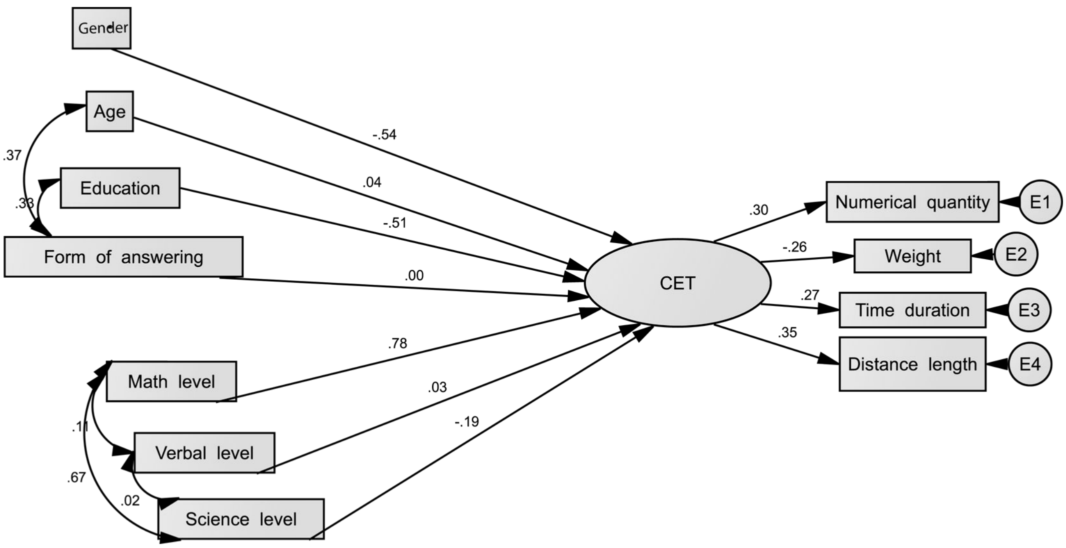

Figure 1. To test the multivariate relations between estimation and cognitive factors, we created a theoretical model.

Note. We used SEM to test our theoretical model. The result indicated that gender, education, and math level predicted estimations. Age, form of answering, and writing level and science level did not. All the values are standardized.

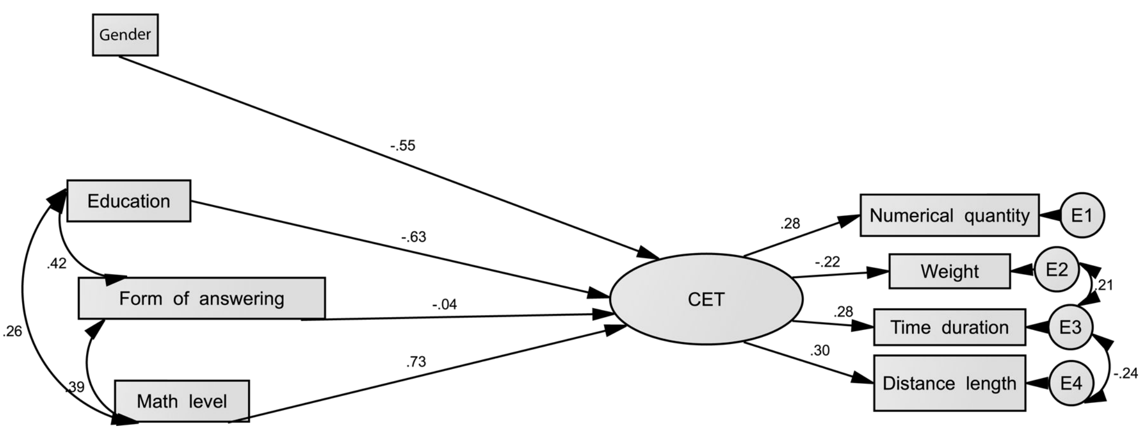

Figure 2. SEM model based on the improvement of the initial model described in Figure 1.

Note. The result indicated that gender, education, and math level predicted estimation performance. Form of answering did not. All the values are standardized.

Discussion

The first goal of Experiment 1 was to create a Hebrew version of the BCET. To do so, we translated the questions to Hebrew and modified some of the questions to fit Israeli culture. Then, we piloted the Hebrew version on a large adult sample. First, similar to previous studies, we discovered that education and gender affected cognitive estimation. Moreover, participants with higher math abilities gave higher estimations than participants with lower math abilities. Given that our calculation of Cronbach's alpha revealed that the distance/ length category did not tap a single estimation mechanism, we will not use it in the analysis described below.

The main goal of the present study was to examine whether cognitive representations of different types of quantities are shared or distinct. According to the SEM, we discovered that numerical quantity is unique, and weight, time, and distance/length all shared some variance. Even if the estimations of all magnitudes originate from a common mechanism (Walsh, 2003), the need for using units of measurement differentiate the various contexts of magnitude. For example, in the estimation of numerical magnitude (How many cookies fit in a cookie jar? ____ cookies), the unit of measurement is part of the question (i.e., “cookies”) and it is very intuitive to use. However, in weight and time estimation, when the units of measurements are not part of the question (How much time will it take to fill a bathtub? _____ minutes), understanding the unit of measurement and fitting it to the estimation adds an extra layer of difficulty and potentially requires more EF. However, understanding the unit of measurement and fitting it to the estimation may also require other constructs, such as sustained attention or IQ.

One of the goals of Experiment 2 was to further investigate the similarities and dissimilarities between representation mechanisms by examining the relations among different categories and general cognitive abilities.

Experiment 2: Understanding the Role of Domain General and Domain Specific Factors in the Cognitive Estimation Task

In the present experiment, we used several tasks to test a few constructs and the different relations between these constructs and the estimation categories. First, there is a general agreement that the cognitive estimation task requires EF (Wagner, MacPherson, Parente, & Trentini, 2011). To test individual differences in EF, we used the Wisconsin Card Sorting Test, which is often used to examine frontal lobe damage in EF weakness (Berg, 1948). Specifically, this card-sorting tasks requires, first, the understanding of an implicit rule and, second, shifting from one rule to another (Berg, 1948). Cognitive estimation requires shifting and nonstructured solutions, thus the Wisconsin Card Sorting Test serves as the best EF task to predict individual differences in estimation abilities.

Moreover, the cognitive estimation task also requires preservation of verbal information in WM and manipulation of verbal information. Hence, to predict estimation performance, we tested individual differences in the verbal WM and central executive component of WM using backward and forward digit recall.

IQ was found to have a significant role in explaining individual differences in cognitive estimation performance in a nonclinical population (O’Carroll, Egan, & MacKenzie, 1994). Thus, to test the relations between IQ and estimation ability, we used the Raven’s Progressive Matrices task to evaluate nonverbal IQ, in an effort to avoid potential bias in assessing verbal IQ in participants with learning disabilities (Penrose & Raven, 1936).

Because we tested ADHD participants, individual abilities in four attentional networks were also evaluated. The cognitive estimation task requires participants to maintain attention during multi-stage long-solution processes; hence, we used only the score of the continuous performance test (CPT) to assess estimation performance.

Finally, as stated, the first aim of this research was to highlight the role of numerical estimation in the cognitive estimation task. To evaluate individual differences in the innate nonverbal quantity representation, we used the ANS task to examine nonsymbolic speeded comparisons between arrays of dots (Halberda et al., 2008).

Method

Participants

This study included 26 college students divided into two groups: an ADHD group, which included 13 adults diagnosed with ADHD (M_{Age} = 23.46 years; *SD* = 4.05; 8 females), and a control group, which included 13 typically developed adults who were matched to the ADHD participants by gender, age, and IQ (M_{Age} = 23.92 years, *SD* = 3.72). ADHD participants were carefully selected according to a clinical assessment carried out by a physician. Moreover, we excluded participants with any comorbidity of ADHD and developmental dyscalculia or developmental dyslexia. All the participants were either paid 90 NIS ($26) for participation in the experiment or received course credit.

Domain General Tasks

Wisconsin Card Sorting Test (WCST; Berg, 1948) — In a computerized version of this task (taken from the PEBL; Mueller, 2012), a number of stimulus cards were presented to the participant. The participant was asked to match the cards, but was not told *how* to match the cards; however, he or she was told whether a particular match was correct or incorrect. We focused on WCST preservative errors, in other words, the immediate repetition of an incorrect response.

Working memory (WM) — For the purpose of this study, our conceptualization of WM came from Baddeley (Baddeley, 2001; Baddeley & Hitch, 1974), who proposed partitioning WM into three components, namely the central executive, the phonological loop, and the visuospatial sketchpad. This original model was updated later with additional components, including the Episodic Buffer, which stores multimodal information and plays a role in awareness (Baddeley, 2000). Due to the strong involvement of the phonological loop and the central executive components in WM, we examined the central executive using digit-span backward[i] and the phonological loop using digit-span forward.

Attention — Tsal, Shalev, and Mevorach (2005) suggested that attention could be divided to four systems: selective attention, executive attention, sustained attention, and orienting of attention and that individual differences in ADHD could be found in any of these four systems. Here we used the same methodology to assess the four systems of attention. To assess the function of selective attention, we used a conjunctive visual search task. The task was to search for a target defined as a specific conjunction of color and shape. To assess the function of executive attention, we used a Stroop-like task. Participants were presented with a single stimulus varying along two dimensions that could elicit conflicting responses. To measure sustained attention, we constructed a vigilance task similar to the continuous performance test. To assess the function of orienting of attention, we used a cost-benefit technique with an exogenous cue. For complete details of these tasks, see Tsal et al. (2005)

Raven's progressive matrices task — We used a computerized version of this test (Raven, 1958) to examine nonverbal intelligence (Penrose & Raven, 1936). The test consists of 60 diagrammatic problems, each with eight possible choices for answers. The computerized version was obtained from J.C. Raven Ltd. and is designed for research purposes only. See Williams and McCord (2006) for the computerized and noncomputerized version of the tests.

Domain Specific Tasks

ANS task — Two sets of overlapping dots (one in yellow and in blue) briefly appeared on a screen (for 300 ms). The participants were required to indicate whether the blue array or yellow array was larger in quantity. Ratios between the sets were manipulated between 1:2, 3:4, 5:6, or 7:8. For every set, the quantity ranged from 5 to 16 dots. To control for possible intervening variables, such as total area and dot size, the trials were split in half. Half of the trials were controlled for area, and the total area of the two sets was identical; the remaining trials were controlled for size, such that the size of the dots in both sets was equal (n = 120). We examined the Weber fraction, the smallest numerical change to a stimulus that can be reliably detected by an individual. Smaller Weber fractions indicate a better individual ability to differentiate between quantities. We used Panamath software to administer the ANS task, for complete details see Halberda et al. (2008).

Procedure

Participants were tested individually in two sessions that lasted approximately 4 hours. In the first session, they performed the attention tasks (i.e., selective attention, executive attention, sustained attention, and orienting of attention). In the second session, they completed the cognitive estimation task, the EF and ANS tasks, and other tasks. The cognitive estimation task was controlled by Googledocs, similar to Experiment 1.

Results

Group Comparison for General Abilities

All participants had IQ scores in the normal range according to Raven's progressive matrices task. Both groups displayed a comparable performance level with regard to neuropsychological background tests, tapping attention span, visual search, executive attention, and spatial attention, except for the continuous attention task, for which the ADHD group had lower performance than the control group (see Table 2).

Table 2

Standardized IQ, Executive Functions, Working Memory, and Attention Scores for Participants in the ADHD and Control Groups

	ADHD		Control		
	M	*SD*	*M*	*SD*	*p*
IQ	65.69	22.83	70.33	20.15	.40
Age	23.46	4.10	23.92	3.73	.77
TOH	1.79	1.14	1.41	1.44	.46
WCST correct	83.77	7.03	79.43	11.55	.46
WCST categories	4.00	0.91	4.08	0.86	.83
WCST failure to maintain category	0.69	0.75	0.23	0.44	.07
WCST preservative error	8.15	2.55	12.62	8.38	.09
Digits forward	37.92	6.34	40.38	5.58	.30
Digits backward	23.31	6.02	29.46	6.59	.02
CPT commission	0.01	0.01	0.01	0.01	.14
CPT omission	0.00	0.01	0.00	0.01	.67
CPT test score	0.19	0.05	0.14	0.02	.00
Stroop-like	0.09	0.04	0.12	0.07	.25
Spatial attention	0.04	0.12	0.09	0.07	.23
Visual search	11.71	4.57	9.54	3.52	.19

Note. TOH = Tower of Hanoi; WCST = Wisconsin Card Sorting Test; CPT = continuous performance task.

In relation to EF functions, the two groups had comparable performances in all the tests (see Table 2), and in relation to WM, the groups' performances were similar with respect to the phonological loop. However, the control group had better performance in the central executive span than the ADHD group (see Table 2).

Regression Analysis

Here, we ran multiple hierarchical regression analyses to predict cognitive estimation for the time, weight, and numerical quantity categories. We omitted the distance category after the Cronbach's alpha analysis. We aimed to explore the effects of EF abilities, basic quantity representations, attention abilities (sustained attention), and IQ on cognitive estimation.

We first created dummy variables for the groups (ADHD: 1, Control: 0) and interaction between groups and the other factors. To test whether numerical preverbal abilities, attention, and IQ, affected estimation performance over and above the influences of group and WM, predictors were included in the blocks in the following order: (a) group, (b) WM, (c) interactions between the group and WM, (d) Weber fraction, (e) interactions between the group and Weber fractions, (f) continuous preference task (CPT) for sustained attention, (g) interaction between the group and CPT, (h) IQ, and (i) interaction between the group and IQ. Hierarchical regression allowed us to examine the specific contribution of every one of the blocks (EF, basic quantity representations, attention, WM, and IQ and their interaction with group) on the dependent variable.

Numerical Estimation

The second step of entering WM significantly increased model fit (ΔR^2 = .25, p < .05). However, both the betas of WM forward (β = -0.34, t = -1.6, p = .12) and backward (β = -0.31, t = -1.2, p = .24) were not significant. In general, better WM was associated with estimations that were closer to the norm means. Additionally, the fifth step of adding the interaction between Weber fractions and group to the model, added significant variability (ΔR^2 = .13, p < .05); the entire model was significant (R^2 = .76, p < .05, df_{total} = 24). Better discriminability was associated with estimations that were closer to the norm means; this trend was found in the ADHD group but not in the control group. None of the other blocks added significant explained variability (Table 3 and Figure 3).

Table 3

Hierarchical Regression Analyses

Model	ΔR^2	p	B	SE	β	t	p	Partial correlation
Step 1: Group	.06	.22						
Group			0.217	0.175	0.250	1.240	.228	.250
Step 2: WM	.25	.04						
Group			0.003	0.192	0.003	0.014	.989	.003
WM F			-0.025	0.015	-0.340	-1.616	.121	-.333
WM B			-0.021	0.017	-0.307	-1.220	.236	-.257
Step 3: WM interactions	.10	.22						
Group			1.942	1.112	2.243	1.747	.097	.372
WM F			0.000	0.023	0.001	0.004	.996	.001
WM B			-0.016	0.027	-0.235	-0.582	.567	-.132
WM F X G			-0.044	0.030	-1.989	-1.481	.155	-.322
WM B X G			-0.007	0.034	-0.202	-0.208	.837	-.048

Model	ΔR^2	*p*	*B*	*SE*	β	*t*	*p*	Partial correlation
Step 4: ANS	.36	.29						
Group			1.915	1.107	2.212	1.730	.101	.378
WM F			0.008	0.024	0.115	0.349	.731	.082
WM B			-0.023	0.028	-0.344	-0.829	.418	-.192
WM F X G			-0.049	0.030	-2.224	-1.642	.118	-.361
WM B X G			-0.000	0.034	0.001	0.001	.999	.000
Weber fraction			0.418	0.385	0.205	1.086	.292	.248
Step 5: ANS interaction	.13	.04						
Group			0.900	1.098	1.040	0.820	.424	.195
WM F			-0.009	0.023	-0.124	-0.392	.700	-.095
WM B			-0.008	0.026	-0.116	-0.298	.769	-.072
WM F X G			-0.024	0.030	-1.067	-0.803	.433	-.191
WM B X G			-0.017	0.032	-0.493	-0.538	.598	-.129
Weber fraction			-0.461	0.524	-0.226	-0.879	.392	-.209
Weber fraction X G			1.365	0.609	0.855	2.242	.039	.478
Step 6: Attention	.08	.20						
Group			1.795	1.123	2.073	1.598	.130	.371
WM F			-0.009	0.021	-0.127	-0.431	.672	-.107
WM B			-0.014	0.024	-0.210	-0.577	.572	-.143
WM F X G			-0.044	0.029	-1.958	-1.483	.158	-.348
WM B X G			-0.020	0.030	-0.560	-0.656	.521	-.162
Weber fraction			-0.418	0.488	-0.205	-0.858	.404	-.210
Weber fraction X G			1.479	0.569	0.927	2.599	.019	.545
CPT			-0.007	0.004	-0.449	-1.913	.074	-.431
Step 7: Attention interaction	.02	.42						
Group			2.017	1.164	2.329	1.732	.104	.408
WM F			-0.008	0.022	-0.107	-0.359	.725	-.092
WM B			-0.010	0.025	-0.154	-0.413	.685	-.106
WM F X G			-0.037	0.031	-1.671	-1.214	.243	-.299
WM B X G			-0.022	0.030	-0.617	-0.715	.486	-.182
Weber fraction			-0.386	0.494	-0.189	-0.782	.447	-.198
Weber fraction X G			1.236	0.643	0.775	1.921	.074	.444
CPT			-0.002	0.007	-0.104	-0.218	.830	-.056
CPT X G			-0.005	0.006	-0.565	-0.839	.415	-.212
Step 8: IQ	.02	.42						
Group			2.080	1.179	2.402	1.765	.099	.427
WM F			-0.007	0.022	-0.097	-0.323	.752	-.086
WM B			-0.012	0.025	-0.173	-0.459	.654	-.122
WM F X G			-0.044	0.032	-1.979	-1.376	.191	-.345
WM B X G			-0.014	0.032	-0.401	-0.440	.667	-.117
Weber fraction			-0.289	0.513	-0.142	-0.564	.581	-.149
Weber fraction X G			1.093	0.673	0.685	1.626	.126	.398
CPT			-0.003	0.007	-0.184	-0.375	.713	-.100
CPT X G			-0.004	0.006	-0.455	-0.655	.523	-.173
IQ			-0.003	0.004	-0.149	-0.832	.419	-.217

Model	ΔR^2	*p*	*B*	*SE*	β	*t*	*p*	Partial correlation
Step 9: IQ interaction	.01	.50						
Group			2.420	1.301	2.795	1.860	.086	.458
WM F			-0.007	0.022	-0.102	-0.332	.745	-.092
WM B			-0.010	0.026	-0.152	-0.392	.701	-.108
WM F X G			-0.045	0.033	-2.020	-1.375	.192	-.356
WM B X G			-0.006	0.034	-0.183	-0.187	.855	-.052
Weber fraction			-0.352	0.531	-0.173	-0.664	.518	-.181
Weber fraction X G			0.971	0.709	0.609	1.370	.194	.355
CPT			-0.001	0.008	-0.083	-0.159	.876	-.044
CPT X G			-0.005	0.006	-0.554	-0.768	.456	-.208
IQ			-0.001	0.005	-0.053	-0.232	.820	-.064
IQ X G			-0.006	0.008	-0.471	-0.682	.507	-.186

Note. CPT = continuous performance task; WCST = Wisconsin Card Sorting Test; TOH = Tower of Hanoi; WM F = working memory forward; WM B = working memory backward; X G = interaction with group.

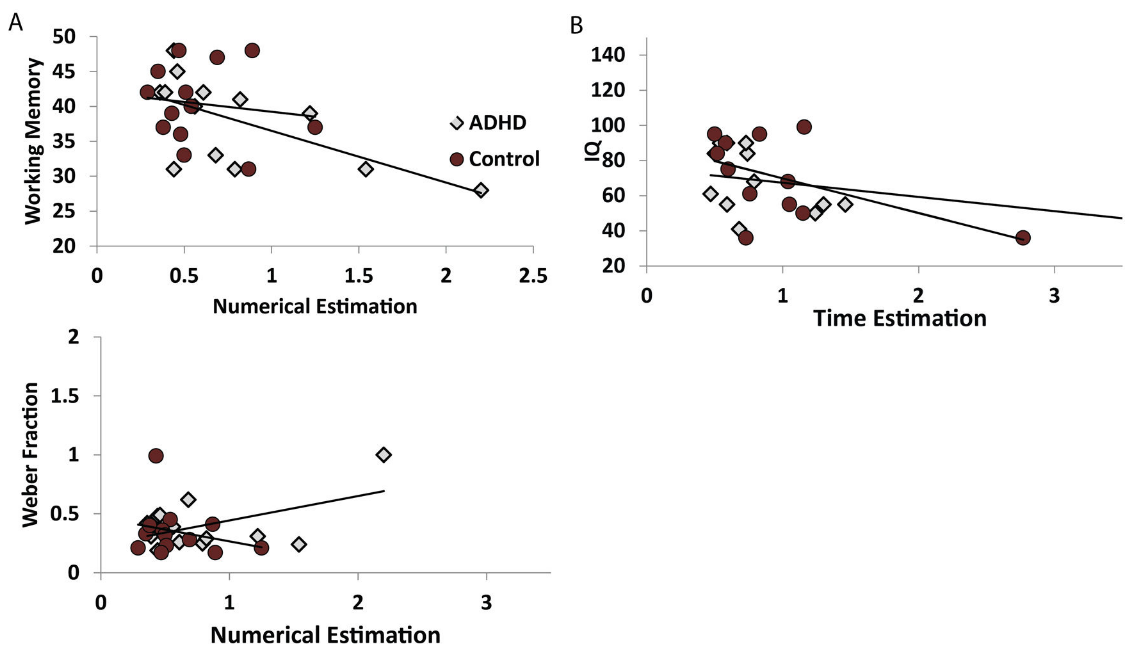

Figure 3. Correlations between estimations and domain specific and domain general factors.

Note. Hierarchical regression was performed on cognitive estimation. Group was defined as a dummy variable. The results indicated that the approximate number sense, a preverbal domain specific ability, predicted numerical estimation. Please note that this tendency was stronger among the ADHD group compared to the control group (top panel A). Moreover, working memory forward was also related to numerical estimation (bottom panel A). However, cognitive estimation of time was predicted by IQ. Please note that this tendency was stronger among the ADHD group compared to the control group (panel B).

Time Estimation

The eighth step, entering IQ, added significant variability ($\Delta R^2 = .28$, $p < .05$); however, the entire model, at that point, was not significant ($R^2 = .51$, $p = .26$, $df_{total} = 24$). Specifically, IQ predicted significant variability (β = -0.63, $t = -2.8$, $p < .05$). In general, higher IQ was associated with estimations that were closer to the norm means. Additionally, the ninth step of adding the interaction between IQ and group to the model, added significant variability (ΔR^2 = .14, p < .05); however, the entire model was still not significant (R^2 = .65, p = .1). Specifically, the interaction between group and IQ predicted significant variability (β = -1.6, t = -2.26, p < .05) in the time estimation category. The relation between IQ and time estimation was stronger in the ADHD group compared to the control group (see Table 4 and Figure 3).

The number of participants was rather small (N = 26), and the number of predictors was rather large. Thus, to understand the nonsignificant results of the regressions presented above, we performed additional hierarchical regressions with fewer predictors, specifically, with (a) group, (b) IQ, and (c) interaction between the group and IQ. Similar to the previous results, at the second step, entering IQ added significant variability (ΔR^2 = .27, p < .001); the entire model, at that point, was significant (R^2 = .28, p < .05, df_{total} = 24). In general, higher IQ was associated with estimations that were closer to the norm means. Additionally, the third step of adding the interaction between IQ and group to the model added significant variability (ΔR^2 = .075, p < .05); the entire model was still significant (R^2 = .35, p < .05).

Table 4

Regression Analyses

Model	ΔR^2	*p*	*B*	*SE*	β	*t*	*p*	Partial correlation
Step 1: Group	.01	.62						
Group			0.228	0.461	0.102	0.494	.626	.102
Step 2: WM	.10	.33						
Group			-0.245	0.564	-0.110	-0.435	.668	-.095
WM F			-0.010	0.045	-0.053	-0.221	.827	-.048
WM B			-0.060	0.049	-0.350	-1.223	.235	-.258
Step 3: WM interactions	.08	.40						
Group			4.340	3.364	1.951	1.290	.213	.284
WM F			0.032	0.069	0.171	0.463	.648	.106
WM B			-0.024	0.082	-0.141	-0.297	.770	-.068
WM F X G			-0.077	0.090	-1.347	-0.851	.405	-.192
WM B X G			-0.056	0.103	-0.618	-0.541	.595	-.123
Step 4: ANS	.01	.59						
Group			4.383	3.429	1.970	1.278	.217	.288
WM F			0.019	0.074	0.102	0.257	.800	.060
WM B			-0.013	0.086	-0.075	-0.151	.882	-.036
WM F X G			-0.069	0.093	-1.204	-0.737	.471	-.171
WM B X G			-0.067	0.107	-0.742	-0.625	.540	-.146
Weber fraction			-0.653	1.193	-0.125	-0.548	.591	-.128
Step 5: ANS interaction	.01	.71						
Group			4.993	3.856	2.244	1.295	.213	.300
WM F			0.029	0.080	0.158	0.366	.719	.088
WM B			-0.022	0.091	-0.129	-0.243	.811	-.059
WM F X G			-0.084	0.104	-1.475	-0.812	.428	-.193
WM B X G			-0.056	0.113	-0.626	-0.500	.623	-.120
Weber fraction			-0.125	1.841	-0.024	-0.068	.947	-.016
Weber fraction X G			-0.821	2.137	-0.200	-0.384	.706	-.093

Model	ΔR^2	*p*	*B*	*SE*	β	*t*	*p*	Partial correlation
Step 6: Attention	.01	.63						
Group			5.890	4.338	2.648	1.358	.193	.321
WM F			0.029	0.082	0.157	0.355	.727	.088
WM B			-0.029	0.094	-0.166	-0.303	.766	-.075
WM F X G			-0.104	0.113	-1.823	-0.918	.372	-.224
WM B X G			-0.059	0.115	-0.652	-0.509	.618	-.126
Weber fraction			-0.082	1.885	-0.016	-0.044	.966	-.011
Weber fraction X G			-0.706	2.199	-0.172	-0.321	.752	-.080
CPT			-0.007	0.014	-0.175	-0.497	.626	-.123
Step 7: Attention interaction	.00	.98						
Group			5.914	4.601	2.659	1.285	.218	.315
WM F			0.029	0.085	0.158	0.344	.735	.089
WM B			-0.028	0.099	-0.163	-0.284	.780	-.073
WM F X G			-0.103	0.121	-1.811	-0.855	.406	-.216
WM B X G			-0.059	0.119	-0.655	-0.493	.629	-.126
Weber fraction			-0.079	1.952	-0.015	-0.040	.968	-.010
Weber fraction X G			-0.732	2.543	-0.179	-0.288	.777	-.074
CPT			-0.006	0.028	-0.160	-0.220	.829	-.057
CPT X G			-0.001	0.023	-0.024	-0.023	.982	-.006
Step 8: IQ	.28	.01						
Group			6.612	3.805	2.972	1.738	.104	.421
WM F			0.037	0.070	0.200	0.527	.606	.140
WM B			-0.042	0.082	-0.245	-0.515	.615	-.136
WM F X G			-0.179	0.103	-3.128	-1.730	.106	-.420
WM B X G			0.024	0.103	0.271	0.237	.816	.063
Weber fraction			0.985	1.655	0.188	0.596	.561	.157
Weber fraction X G			-2.304	2.171	-0.562	-1.061	.307	-.273
CPT			-0.019	0.024	-0.503	-0.818	.427	-.214
CPT X G			0.010	0.019	0.448	0.515	.615	.136
IQ			-0.034	0.012	-0.639	-2.832	.013	-.604
Step 9: IQ interaction	.14	.04						
Group			9.746	3.620	4.381	2.692	.018	.598
WM F			0.034	0.062	0.182	0.547	.594	.150
WM B			-0.029	0.072	-0.167	-0.398	.697	-.110
WM F X G			-0.187	0.091	-3.273	-2.057	.060	-.496
WM B X G			0.095	0.096	1.052	0.990	.340	.265
Weber fraction			0.404	1.477	0.077	0.274	.789	.076
Weber fraction X G			-3.430	1.972	-0.837	-1.739	.106	-.434
CPT			-0.005	0.022	-0.141	-0.250	.807	-.069
CPT X G			0.002	0.017	0.090	0.115	.910	.032
IQ			-0.016	0.013	-0.294	-1.178	.260	-.311
IQ X G			-0.053	0.023	-1.691	-2.263	.041	-.532

Note. CPT = continuous performance task; WCST = Wisconsin Card Sorting Test; TOH = Tower of Hanoi; WM F = working memory forward; WM B = working memory backward; X G = interaction with group.

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Weight Estimation

None of the blocks reached significance (see Table 5).

Table 5

Regression Analyses

Model	ΔR^2	*p*	B	*SE*	β	*t*	*p*	Partial correlation
Step 1: Group	.07	.206						
Group			-0.224	0.172	-0.262	-1.302	.206	-.262
Step 2: WM	.06	.521						
Group			-0.274	0.215	-0.321	-1.278	.215	-.269
WM F			-0.017	0.017	-0.234	-0.987	.335	-.211
WM B			-0.001	0.019	-0.018	-0.065	.949	-.014
Step 3: WM interactions	.02	.836						
Group			-0.953	1.331	-1.116	-0.716	.483	-.162
WM F			-0.028	0.027	-0.397	-1.042	.310	-.233
WM B			0.002	0.032	0.023	0.047	.963	.011
WM F X G			0.020	0.036	0.932	0.571	.574	.130
WM B X G			-0.004	0.041	-0.130	-0.111	.913	-.025
Step 4: ANS	.12	.110						
Group			-1.001	1.271	-1.173	-0.788	.441	-.183
WM F			-0.014	0.027	-0.192	-0.501	.623	-.117
WM B			-0.011	0.032	-0.172	-0.357	.726	-.084
WM F X G			0.011	0.035	0.508	0.322	.751	.076
WM B X G			0.008	0.040	0.235	0.205	.840	.048
Weber fraction			0.743	0.442	0.369	1.680	.110	.368
Step 5: ANS interaction	.03	.376						
Group			-0.476	1.402	-0.557	-0.339	.738	-.082
WM F			-0.005	0.029	-0.067	-0.163	.873	-.039
WM B			-0.019	0.033	-0.292	-0.581	.569	-.139
WM F X G			-0.002	0.038	-0.100	-0.058	.954	-.014
WM B X G			0.017	0.041	0.494	0.417	.682	.101
Weber fraction			1.198	0.669	0.596	1.790	.091	.398
Weber fraction X G			-0.707	0.777	-0.449	-0.910	.376	-.215
Step 6: Attention	.15	.059						
Group			-1.675	1.417	-1.962	-1.182	.254	-.283
WM F			-0.004	0.027	-0.063	-0.167	.870	-.042
WM B			-0.011	0.031	-0.163	-0.350	.731	-.087
WM F X G			0.024	0.037	1.113	0.659	.519	.163
WM B X G			0.020	0.038	0.585	0.537	.599	.133
Weber fraction			1.141	0.616	0.567	1.854	.082	.421
Weber fraction X G			-0.861	0.718	-0.547	-1.199	.248	-.287
CPT			0.009	0.004	0.611	2.033	.059	.453

Model	ΔR^2	*p*	B	*SE*	β	*t*	*p*	Partial correlation
Step 7: Attention interaction	.07	.178						
Group			-1.222	1.412	-1.431	-0.865	.400	-.218
WM F			-0.002	0.026	-0.022	-0.059	.953	-.015
WM B			-0.003	0.030	-0.048	-0.104	.919	-.027
WM F X G			0.037	0.037	1.707	1.009	.329	.252
WM B X G			0.016	0.037	0.466	0.439	.667	.113
Weber fraction			1.207	0.599	0.600	2.015	.062	.462
Weber fraction X G			-1.357	0.780	-0.863	-1.739	.102	-.410
CPT			0.020	0.009	1.326	2.269	.038	.506
CPT X G			-0.010	0.007	-1.170	-1.412	.178	-.343
Step 8: IQ	.10	.086						
Group			-1.065	1.313	-1.247	-0.811	.431	-.212
WM F			0.000	0.024	0.003	0.008	.994	.002
WM B			-0.006	0.028	-0.096	-0.224	.826	-.060
WM F X G			0.020	0.036	0.934	0.575	.575	.152
WM B X G			0.035	0.035	1.010	0.982	.343	.254
Weber fraction			1.447	0.571	0.719	2.535	.024	.561
Weber fraction X G			-1.712	0.749	-1.088	-2.285	.038	-.521
CPT			0.017	0.008	1.124	2.034	.061	.478
CPT X G			-0.008	0.007	-0.892	-1.139	.274	-.291
IQ			-0.008	0.004	-0.375	-1.850	.086	-.443
Step 9: IQ interaction	.04	.261						
Group			-1.695	1.402	-1.985	-1.209	.248	-.318
WM F			0.001	0.024	0.012	0.035	.972	.010
WM B			-0.009	0.028	-0.136	-0.322	.752	-.089
WM F X G			0.022	0.035	1.010	0.629	.540	.172
WM B X G			0.021	0.037	0.601	0.560	.585	.153
Weber fraction			1.564	0.572	0.778	2.735	.017	.604
Weber fraction X G			-1.485	0.764	-0.944	-1.945	.074	-.475
CPT			0.014	0.008	0.935	1.643	.124	.415
CPT X G			-0.006	0.007	-0.705	-0.893	.388	-.240
IQ			-0.011	0.005	-0.555	-2.203	.046	-.521
IQ X G			0.011	0.009	0.886	1.175	.261	.310

Note. CPT = continuous performance task; WCST = Wisconsin Card Sorting Test; TOH = Tower of Hanoi; WM F = working memory forward; WM B = working memory backward; X G = interaction with group.

Group Comparison for Main Task

The BCET is composed of four different categories. We examined group differences (ADHD/ Control) in cognitive estimation as a function of estimation category. A two-way analysis of variance (ANOVA) was performed on the mean individual absolute distance from the mean of the norms, with question category (quantity, weight, distance/length, and time/age) as the within-subject factor and group (ADHD or control) as the between-subject factor. Neither the effect of category, $F(3, 72) = 2.14$, $p = .32$, $\eta_p^2 = .14$, nor the effect of group, $F(1, 24) = 0.28$, $p = .60$, $\eta_p^2 = .12$, reached significance. Similarly, the interaction between category and group was not significant, $F(3, 72) = 0.73$, $p = .29$, $\eta_p^2 = .08$ (see Figure 4).

Additionally, a simple *t* test did not reveal group differences (i.e., ADHD vs. control) between the general BCET score, $t(24) = 0.25$, $p = .8$.

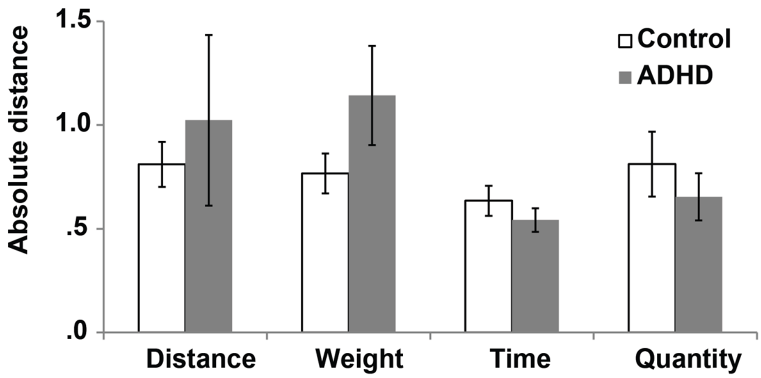

Figure 4. Mean absolute distance from the norms for the Hebrew-version of the Biber cognitive estimation task as a function of group (ADHD and Control) and estimation category.

Note. The results indicated that ADHD participants had comparable cognitive estimation abilities in all the estimation categories.

Discussion

The first goal of Experiment 2 was to verify the dissociation between cognitive representations of different types of quantities, as presented in Experiment 1. By using multiple hierarchical regressions, we discovered that the different domain general and domain specific abilities predicted performance in the cognitive estimation categories. In the first experiment, we discovered that all the estimation categories shared some variance; however, the relations were stronger between time, weight, and distance compared to numerical estimation. We suggest that numerical estimation is not based on an external unit of measurement, such as hours, kilogram, or meters, and, thus, represents a more "pure" numerical estimation. In line with this view, first, we discovered that numerical estimation was associated with innate preverbal quantity representations and WM. However, time estimation was associated with IQ, demonstrating dissociations between estimation categories.

The second goal of Experiment 2 was to examine cognitive estimation in a group of college students diagnosed with ADHD, a frequently diagnosed neurodevelopmental disorder that is characterized by EF deficits in planning, WM, response inhibition, and sustained attention. Contrary to our assumptions, the ADHD group and the typically developed group had comparable performances in cognitive estimation.

Therefore, the main goal of Experiment 3 was to replicate these results (e.g., lack of group differences in the cognitive estimation of different categories) by using a new test of cognitive estimation. To do so, we created a new cognitive estimation test with more questions in every category.

Experiment 3: Testing Group Effects Between ADHD Participants and Control Participants in an Extended Cognitive Estimation Task

Method

One of the aims of Experiment 2 was to test ADHD participants in a cognitive estimation task. We used the Hebrew translation of the BCET, a test that contained four categories of estimation: quantity, weight, distance/length, and time/age. Contrary to our prediction, in Experiment 2, we obtained intact estimation abilities in the ADHD group in every one of the categories. However, each category contained only five questions. Accordingly, we wanted to make sure that the lack of group differences was not due to a lack of statistical power. Therefore, in Experiment 3, we presented estimation questions from only three extended categories: time, quantity, and weight. We ran the new test on a group of 89 adults. We used the same methodology that was used in Experiment 1. The results and the translation of the questions to English can be seen in Table 6.

Table 6

Item Statistics for the Development Sample, Experiment 3

Num	Category	Units	*M*	*SD*	Item
1	Weight	Grams	1579.4	1614.6	How much does a pair of men's shoes weigh?
2	Weight	Kilograms	2.4	2.1	How much does a wool coat weigh?
3	Weight	Grams	1185.3	1169.6	How much does a bouquet of flowers weigh?
4	Weight	Kilograms	55.9	62.1	How much does a two-seater couch weigh?
5	Weight	Kilograms	7.2	10.1	How much does a desktop computer weigh?
6	Weight	Grams	2433.9	2123.5	How much does a folding chair weigh?
7	Weight	Kilograms	33.7	136.1	How much does a supermarket cart weigh?
8	Weight	Grams	2695.7	4306.8	How much does a wall clock weigh?
9	Weight	Kilograms	3.0	3.2	How much does a medium-sized framed picture weigh?
10	Weight	Grams	1052.9	985.0	How much does a medium-sized book weigh?
11	Weight	Kilograms	32.6	40.7	How much does an office refrigerator weigh?
12	Weight	Grams	505.8	654.0	How much does falafel in a pita weigh?
13	Weight	Grams	58.5	63.5	How much does one egg weigh?
14	Weight	Kilograms	3.0	3.1	How much do a dozen apples weigh?
15	Quantity	Slices	128.2	341.4	How many slices of bread can you spread with chocolate spread until the container of spread is empty?
16	Quantity	Brushings	123.3	126.7	How many times can you brush your teeth with one tube of toothpaste?
17	Quantity	Candies	96.7	91.9	How many toffees are in a large package?
18	Quantity	Tablespoons	14.5	15.5	How many tablespoons of cottage cheese are in a standard package?
19	Quantity	Flowers	130906.4	861706.9	How many flowers are there on an almond tree during blooming?
20	Quantity	Slices	22.0	8.3	How many slices of bread are there in a standard loaf?
21	Quantity	Tablespoons	116.5	190.6	How many tablespoons of sugar are there in a standard package?
22	Quantity	Grains	1328795.0	8684686.1	How many grains of rice are there in a standard package?
23	Quantity	Cornflakes	147881.8	864028.3	How many cornflakes are there in a box?
24	Quantity	Cookies	41.6	37.8	How many cookies fit in a cookie jar?
25	Quantity	Hair washings	57.7	51.3	How many times can you shampoo your hair from a big shampoo bottle?

Num	Category	Units	*M*	*SD*	Item
26	Quantity	People	32844.6	52001.6	How many people can be seated in a large soccer stadium?
27	Quantity	Seeds	1781.3	8819.1	How many black seeds are there in a small bag?
28	Quantity	Sticks	138.9	146.1	How many sticks of spaghetti are there in a half kilo package?
29	Time	Days	11.8	6.9	How long does it take milk to spoil in the refrigerator?
30	Time	Hours	4.4	6.2	How long does it take to paint a medium-sized room?
31	Time	Minutes	24.1	21.9	How long does it take one man to build a tent?
32	Time	Minutes	2.7	2.0	How long does it take to boil water in an electric kettle?
33	Time	Hours	72.2	192.2	How long does it take to solve a puzzle?
34	Time	Minutes	13.3	12.1	How long does it take to fill a bathtub with water?
35	Time	Minutes	9.7	13.1	How long does it take to inflate an electric blow-up mattress?
36	Time	Hours	189.4	818.8	How long can a flashlight remain lit until the battery dies?
37	Time	Days	6.4	4.5	How long can flowers stay in a vase before they wilt?
38	Time	Days	4.5	6.9	How long does it take a carpenter to build a large closet?
39	Time	Minutes	4.2	2.8	How long does it take to fill up a car with gas?
40	Time	Minutes	2.7	2.9	How long does it take to swim across a pool at medium speed?
41	Time	Seconds	40.2	50.7	How long does it take to blow up a balloon?
42	Time	Minutes	20.4	25.2	How long does it take to build a shelf?

Participants

The study included 26 college students divided into two groups: an ADHD group, which included 13 adults diagnosed with ADHD (M_{Age} = 23.46 years; *SD* = 4.05; 8 females), and a control group, which included 13 typically developed adults who were matched to the ADHD participants by gender, age, and IQ (M_{Age} = 24.43 years, *SD* = 3.72). ADHD participants were carefully selected in a process similar to the participant selection used in Experiment 2.

Procedure

The cognitive estimation task was controlled by Googledocs. In the cognitive estimation task, participants were required to answer a set of 42 estimation questions for three different categories: quantity, weight, and time.

Results

A two-way analysis of variance (ANOVA) was performed on the average z score of the estimations with question type (quantity, weight, and time) as the within-subject factor and group (ADHD or control) as the between-subject factor. Neither the effect of category, $F(2, 48) = .50$, $p = .61$, $\eta_p^2 = .20$, nor the effect of group, $F(1, 25) = 0.45$, $p = .51$, $\eta_p^2 = .02$, reached significance. Similarly, the interaction between category and group was not significant, $F(2, 48) = 0.51$, $p = .60.$, $\eta_p^2 = .02$.

Figure 5 presents the group mean estimations for category.

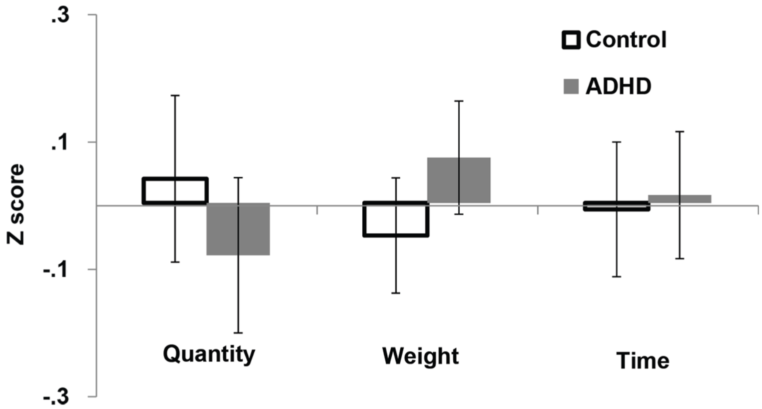

Figure 5. Mean estimations in different categories as a function of group.

Note. The results indicated that ADHD participants had comparable cognitive estimation abilities in all the estimation categories.

Discussion

The main goal of Experiment 3 was to verify the lack of group differences in cognitive estimation, which was observed in Experiment 2, between students diagnosed with ADHD and a match of typically developed students. To do so, we created a new cognitive estimation task with three categories: weight, time, and quantity. We excluded the distance/length category due to the results of Experiment 1. Before starting Experiment 3, we created the new cognitive estimation task and collected data from the adult sample.

Similar to Experiment 2, there were no significant group differences across and within estimation categories, indicating that college students diagnosed with ADHD have intact cognitive estimation abilities. However, our ADHD group also had intact EF abilities (except for central executive deficits). Hence, the preservation of cognitive estimation abilities among participants who have been diagnosed with ADHD could be a result of the group sample of college students and should be verified in future studies.

General Discussion

The main goal that guided the present study was to examine whether cognitive representations of different types of quantities are shared or distinct. ATOM proposed a shared cognitive mechanism for the processing of different types of quantities (such as time, space/ and numerical quantities; Walsh, 2003), which is driven by the analog magnitude representation mechanism. Considering the presumed functional role of the analog magnitude representation mechanism in cognitive estimation abilities, the BCET, composed of different categories (such as time, numerical quantities, length, and weight), served as a real-life examination of ATOM. The first experiment's results revealed that all the cognitive estimation categories shared some variance and that there was more shared variance between time, weight, and distance. The numerical estimation shared less variance with the others. We proposed that time, weight, and distance needs the use of external units of measurement.

Although all of the cognitive estimation questions required multiple stages to reach a solution, the number of steps changed by category. Specifically, numerical quantity estimation needed fewer steps to reach a solution than time, weight, or distance estimation. For example, to answer the numerical quantity question, "How many times can you brush your teeth with one tube of toothpaste?" participants had to first create a mental image of the tube of toothpaste and then perform some kind of calculation involving the size of the toothbrush. This process requires a minimal level of IQ or EF as well as numerical estimation. However, in the case of estimation of time, EF is needed. For example, to answer the time estimation question "How much time does it take to fill a bathtub?" participants had to perform four steps: (a) create a mental image of filling a bathtub, (b) estimate the time that it would take, (c) choose the correct unit of measurement, then (d) divide the estimated time by the correct unit of measurement. These two extra steps require additional EF.

Indications for heterogeneity of estimation categories were also confirmed in Experiment 2. Importantly, the results indicated that when all the other factors remained constant, a unique relation was found between numerical estimation and domain specific abilities (i.e., ANS). Additionally, an exclusive relation was found between time estimation and domain general abilities (IQ). Finally, ADHD participants, across two different studies and different categories, showed intact cognitive estimation abilities.

Multiple Representations Mechanisms Are Involved in Magnitude Estimation

ATOM proposes a common mechanism for the processing of all quantities such as time, space, and numerals (Walsh, 2003). This common mechanism develops from a single magnitude system operating from birth. However, the experiments that have tested similarities and dissimilarities between magnitude estimations have been based on procedures that do not require a verbal tag for quantities (Cohen Kadosh et al., 2005), for example, comparisons between lengths of a lines, durations, or nonsymbolic dot arrays, all of which are very different than cognitive estimation. Verbal reports are different between categories and relate to the use of measurement units. Therefore, we suggest that only numerical estimation, which does not require the use of measurement units, is the best fit for the shared innate models (ATOM). Importantly, we discovered that numerical quantity estimations were uniquely supported by a preverbal ability to intuitively understand approximate quantity and the relation between quantities (ANS), which was not the case with the other categories.

Mechanism of Analog Magnitude Representation in the Cognitive Estimation Task

Since the first cognitive estimation tasks were introduced, EF was commonly believed to support cognitive estimation abilities (Shallice & Evans, 1978). However, only a few studies looked at the results of the cognitive estimation tasks as reflecting number processing abilities that were based on the analog magnitude representation mechanism. The relation between numerical abilities and cognitive estimation task performances was first discussed in a case study of a patient (C.G) who had classical signs of Gerstmann's Syndrome including dense acalculia. In the cognitive estimation test, all of her responses to the numerical items were extreme approximations in relation to the normative sample (Cipolotti, Butterworth, & Denes, 1991). Next, Kopera-Frye, Dehaene, and Streissguth (1996) examined number processing and cognitive estimation in a group of participants with prenatal alcohol exposure, indicating particular difficulties in calculation and estimation tests. The greatest impairment, compared to all the other numerical and arithmetical tasks, was found in the cognitive estimation test (Kopera-Frye et al., 1996). In another related study (Liss, Fein, Bullard, & Robins, 2000), cognitive estimation abilities were tested in participants with pervasive developmental disorders using the same version of the cognitive estimation task that was used in the present study (namely, the BCET). In addition to the cognitive estimation questions, a standardized math test (key math), an estimation math test, and an EF test (Wisconsin Card Sorting Test) were administered. The relation between math abilities and cognitive estimation abilities was found to be positive and significant (r = .72, p < .01). Similarly, the relation between math estimation and cognitive estimation was also found to be high and significant (r = .72, p < .01). These correlations were as meaningful as the correlations between EF and cognitive estimation (r = .77, p < .01). Thus, mathematical achievement as well as EF can play a significant role in the explained variability of the cognitive estimation abilities.

Recently, Bisbing and colleagues (2015) examined the role of EF and number knowledge in cognitive estimation by assessing cognitive estimation in patients with prefrontal cortex disease due to behavioral variant frontotemporal dementia (bvFTD) and patients with parietal disease and weakness in math due to corticobasal syndrome (CBS), influence EF or posterior cortical atrophy (PCA), influence number processing abilities. Both bvFTD and CBS/PCA patients had significantly more difficulty with cognitive estimation than the control group. The results related BCET weakness to gray matter atrophy in the right lateral prefrontal cortex or atrophy in the right inferior parietal cortex. These results are consistent with the hypothesis that a frontal-parietal network plays a crucial role in cognitive estimation. Importantly, here, we discovered that math achievements (according to self-reports), but not writing achievements, predicted performance for cognitive estimations.

Intact Cognitive Estimation Abilities Among ADHD Participants

ADHD is defined as a frontal lobe syndrome based on a unitary core deficit in behavioral inhibition (Barkley, 1997). Cognitive estimation tests were mostly used to examine special populations with executive function weakness (Shallice & Evans, 1978). Therefore, due to EF weakness, we expected that ADHD participants would show extreme approximations relative to control participants. However, across two experiments, we found intact estimation abilities in ADHD participants compared to control participants. Several different reasons explain these results. First, ADHD is a neurodevelopment disorder, with compensatory mechanisms that develop throughout childhood. These compensatory mechanisms play a significant role in university students with ADHD, which could potentially mask the differences between the groups. Additionally, contrary to the definition of ADHD as a frontal lobe syndrome, in the present study, only a few domain general differences were found between the groups in the EF and the attention tasks. ADHD participants only had lower central executive abilities compared to the control participants. Hence, the lack of differences between domain general abilities could be the source of intact cognitive estimation abilities found here.

Limitations

A few limitations should be taken in to account in the interpretation of the data of the first experiment, namely sample selection and size: More than half of the participants in Experiment 1 were college students, and the sample size was small (n = 95). We hope that future studies will replicate the present results with a larger sample size and population heterogeneity. Additionally, the sample size in Experiments 2 and 3 was also rather small (13 participants in each group). Although we found no evidence of cognitive estimation deficits in ADHD, this is not full evidence that ADHD will not show estimation deficits in real life or with a noncollege student sample.

Conclusions

The present study examined whether cognitive representations of different magnitudes are shared or distinct. The BCET is a cognitive estimation test that includes estimation questions in a few categories such as time, numerical quantity, weight, and length. We discovered dissociations between BCET categories: quantity, time, distance, and weight estimations were found to be different. We discovered that all of these categories shared some variance; however, time, distance, and weight were more similar to one another than numerical estimation. We suggest that all of the categories – with the exception of numerical estimation – require the use of a unit of measurement. Thus, numerical estimation represents a more pure estimation than the other categories. This result was confirmed in Experiment 2: Numerical estimation was supported by a preverbal, innate ability to understand quantity, whereas time estimation was supported by IQ. Following these results, the present study proposed that the cognitive estimation task is not based on a unitary mechanism and involves (a) numerical estimation, (b) EF, and (c) IQ.

Notes

i) Please note that the central executive component is involved during the manipulation of information; there is a current debate on whether reporting digits backward is considered to be a manipulation of information and thus tests the central executive, or whether it tests only the phonological loop and the load on the visuospatial process (St Clair-Thompson & Allen, 2013).

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Competing Interests

The authors declare that no competing interests exist.

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