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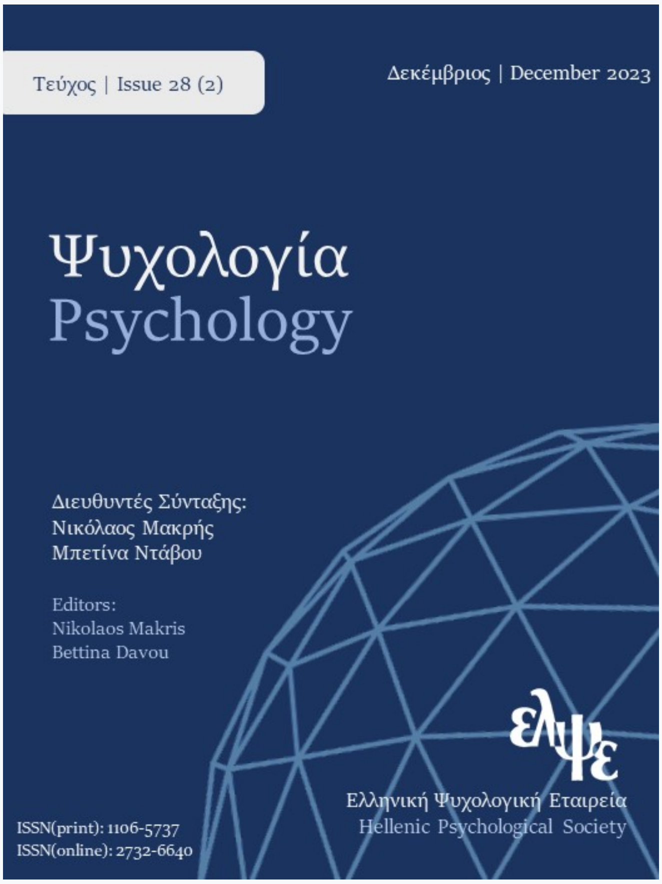

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Exploring the relationship between visual inspection time task and intelligence in young children

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KEYWORDS

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ABSTRACT

Inspection time task (IT) indexes individual differences in perceptual discrimination speed and it is a reliable predictor of psychometric intelligence However, the reasons underlying the relationship between IT and intelligence are not clear, because few studies investigated factors shared by both of them. This study examined how performance on a modified version of the inspection time task relates to individual differences in attentional control and how this relation is affected by age. A total of 157 children from 7 through 18 years were tested in a visual inspection time task, a Go/no-go reaction time task, a letter-matching task, and the Wechsler Abbreviated Scale of *Intelligence* (*WASI*). Diffusion modeling showed that IT captures top-down sensory and attentional processes underlying the IT-IQ relation and that individual differences in drift rate of ECTs predict individual differences in intelligence. Therefore, IT and attention make unique contributions to the prediction of IQ variability.

Introduction

In their attempt to elucidate the nature of general intelligence (g), researchers searched for elementary cognitive correlates of g, such as processing speed, working memory, and attentional capacity. Based on more than 40 years of research, processing speed is considered an established cognitive correlate of psychometric intelligence (Sheppard & Vernon, 2008). Processing speed is typically assessed by cognitively simple tasks such as the Inspection Time task (IT). IT is a specific form of the backward masking paradigm which estimates the minimum amount of exposure time needed to reliably perceive a very simple stimulus (Deary & Stough, 1996; Grudnick & Kranzler, 2001). Variations of the IT paradigm have been used to disentangle the IT-IQ correlation. Two variations of the IT task dominated, the method of constant stimuli requires the presentation of target stimulus at various stimulus onset asynchronies (SOAs) in a random or fixed order and the staircase procedure method in which the SOAs are adapted according to the participant's success rate (Burns, 2008). Here we extend these methodologies using a modified version of the IT task in which we collect reaction times by asking participants to make speeded decisions, in addition to inspection times.

In the visual IT task, the Greek letter pi (Π) with one of two vertical lines longer than the other is presented and participants are asked to indicate which one is longer (or shorter). This task is used to measure inspection rather than reaction times (RTs). That is the intervals between the onset of the stimulus and the onset of a visual mask. IT is used as an index of individual differences in perceptual discrimination speed (Luciano et al., 2005) and it reliably accounts for the relationship between processing speed and psychometric intelligence (Deary, 2001; Jensen, 2006).

The high correlation between performance on this simple two-choice discrimination task and performance on complex non-speeded problem-solving tasks, such as Wechsler intelligence scales or Raven's Progressive Matrices, is one of the most intriguing relations found in the field of individual differences. Among elementary cognitive tasks (ECTs) IT yields the highest and most stable correlations with IQ, and it is thought to assess perceptual speed or general speediness (Carroll, 1993). Previous studies showed a moderate association (r=~-.3 - -.5) between IT and intelligence [2]. Higher correlations have been reported when special groups are tested, such as individuals with intellectual disabilities or university students (Grudnick & Kranzler, 2001). A large volume of research (Edmonds et al., 2008; Grudnick & Kranzler, 2001) indicated that IT improves across the age range of 7 to 18 years, it is related to cognitive abilities in both childhood and adulthood, it is more strongly related to nonverbal rather than verbal IQ, and it is moderately heritable. Both genetic and non-shared environmental factors underlie these relations.

Although extensive, the evidence about the locus of the IT–IQ association is inconclusive (Grudnick & Kranzler, 2001; Nettelbeck, 2001). Obviously, locating IT within the factor structure of intelligence is not an easy task (Nettelbeck, 2001; van Leeuwen et al., 2007). Much of the available literature on the IT task has emphasized its perceptual nature and purity because it avoids mixing cognitive process with motor responses. Several studies found that the IT loads on a 'cognitive speediness' factor (Carroll, 1993; Hunt, 2011), but others suggested that IT is a measure of the speed of sensory processing (Burns et al., 1998). Sheppard and Vernon (2008), based on a meta-analysis of a large number of studies, classified speed measures into five categories, one of them being IT. The others are reaction time, general speed of processing, speed of short-term memory processing, and speed of long-term memory retrieval. They found that measures in all five categories correlated with IQ to some degree. Unfortunately, they did not provide any information about the relations between the five categories.

The inconsistent IT-IQ correlation may be caused by factors other than mental speed which underlies both IT and IQ. These other factors must be specified if the IT-IQ correlation is to be adequately interpreted. Attentional capacity may be one of these factors (Nettelbeck, 2001). Bors et al. (1999) reported that attentiveness contributes to individual differences in IT and that other processes involved that may relate to mental speed contribute to the IT–IQ correlation. The study by Hutton et al. (1997) offers probably the most comprehensive empirical analysis of the possible mediational role of attention on the IT-IQ association. They found a correlation of −.46 between IT and performance on Raven's Colored Progressive Matrices among 8–11-year-olds after controlling for differences on five tests of selective and sustained attention and attentional switching. Study results suggested that both IT and attention contributed about equally to individual differences in intelligence. However, the study did not examine the possible relevance of focused attention. Hill et al. (2011) examined the IT-IQ relation using the ERPs methodology and suggested that the link between IT and g is associated with individual differences in directing attention to stimulus. Fox et al., (2009) presented similar findings.

This evidence suggests that different speed measures evaluate different aspects of mental speed, and attentiveness has some impact on the IT-IQ association in children and adolescents: Attentional control channels processing of incoming information by directing them to relevant goals and responses (Astle et al., 2012). This selection could be driven bottom-up by salient characteristics of stimulus in the environment or by endogenous top-down task-relevant biases. It seems also that our ability to attend relevant stimuli in the visual field affects the speed and accuracy of our responses in detection and discrimination tasks as well as the ability to access representations held in memory (Astle et al., 2012).

Hence, we hypothesize that attentional control is involved in IT execution. This study aimed to demonstrate the possible mediational effects of attentional capacity on the IT-IQ association. We tested two alternative hypotheses in this regard: On the one hand, IT captures low-level physiological processes underlying rapid, automatic extraction of critical information that is made available to hierarchically higher processes of intelligence. This is the bottom-up interpretation assuming that the direction of causality runs from IT to IQ. On the other hand, IT may itself reflect the effects of higher-level cognitive processes, such as strategy use and attentiveness, on the performance of lower-level processes. This is the top-down interpretation assuming that attentional capacity mediates the IT-IQ association by enabling the engagement of strategies and rapid scanning of represented information.

Further, we assume that two of the five categories of speed measures proposed by Sheppard and Vernon (2008), speed of short-term memory processing and speed of long-term memory retrieval require some attentiveness. For instance, the letter-matching task developed by Posner et al. (1969) is used as an index of the speed of accessing information stored in long-term memory. This task usually includes two treatment levels: In the first, participants must judge if the stimuli are *physically identical* (PI-Test), and in the second, they must judge if the stimuli *are semantically identical* (name identity or NI-Test). In the first test, the participants decide based on visual discrimination only, the second test requires them to access highly overlearned information stored in long-term memory (i.e. letters of the alphabet). The difference in the reaction-time for the two treatment levels is, therefore, considered as a measure of the speed of retrieval from long-term memory contents (Hunt, 1980). In the present study we added a third condition in which participants were asked to judge whether the stimuli belong to the same symbolic system, alphabetic or numeric (*symbolically identical*, LI test). Therefore, this condition asks participants to discriminate visually between the two stimuli but also access relevant information stored in the long-term memory in order to decide whether the two stimuli belong or not in the same symbolic system. We assume that this condition is more demanding than the PI test and less demanding than the NI test. Thus, it is assumed that the physical identity condition (PI) mainly stimulates perceptual processes, whereas the name identity (NI) and symbolical identity (LI) stimulate access to information stored in long-term memory. Neubauer et al., (1997) surveyed several studies and found a correlation of -0.23 between the mean reaction time of the PI condition and intelligence scores. A somewhat higher negative correlation (-0.33) was found for the mean reaction time in the NI condition (Altmeyer et al., 2009). Based on these findings we may assume that the Posner task addresses attentiveness related to both perceptual and memory processes. Specifically, we assume that the three conditions reflect how a mechanism of attentional control affects the speed and accuracy of responses in both detection and discrimination tasks.

In the Go/no-go paradigm participants are presented with a series of stimuli and instructed to respond as quickly as possible when they see a 'go' stimulus and to refrain from responding when they see a 'no-go' stimulus. This paradigm has been extensively used to study attentional control. Gomez et al. (2007) concluded that the Go/no-go procedure is just a type of two-choice task in which each of the two responses, go and no-go, is associated with a different decision boundary. Reaction times to the 'go' treatment yield an index of processing speed under sustained concentration conditions, accuracy in the 'no-go' treatment yields an index of inhibitory control. We can assume that mixing the two indexes reflects individual differences in speed of processing under sustained attention functioning.

The diffusion model

The diffusion model offers a framework to account for data in which a speeded decision involving two alternative choices is under consideration (Ratcliff et al., 2016). The diffusion model assumes that this kind of binary decision can be considered as a function of a continuous process that includes two components, a drifting sub-process and normally distributed random noise. The drifting sub-process includes the speed and direction of information accumulation as the thinker attempts to decide between the two alternatives. The attempt to decide when repeatedly facing the same stimulus or type of stimulus might produce different responses varying in reaction time. The differences between these reaction times determine the second component of the diffusion model, that is, random noise.

The diffusion model is characterized by several parameters and has several advantages. First, it relates speed and accuracy scores for elementary cognitive tasks thereby allowing different cognitive processes to be mapped onto different meaningful parameters, these parameters can be used for testing and confirmation of specific theories (Voss et al., 2015). Second, it offers better estimates of the evidence derived from decision process by fitting predicted to empirical reaction time distributions (Voss et al., 2004).

The key parameters of a diffusion model are: (1) The drift rate (v) which reflects the speed of information processing, the drift rate captures factors affecting information accumulation and quantifies the relative amount of information uptake, small drift rates near 0 are connected with long reaction times and high error rates, while large drift rates are indicative of shorter reaction times and lower error rates. (2) The decision boundary (α) which quantifies the decisional style of the subject and determines the speed-accuracy trade-off, slow but accurate responses lead to large estimates of α, whereas quick-inaccurate responding gives small values of α. (3) The starting point (z) or bias which indicates the amount of information required to reach a decision, reflects the starting point at time 0 when information accumulation starts, z is inherently linked with α, and usually takes the value .05α which reflects an unbiased decision process. (4) The time constant (t_0) which represents the duration of all nondecisional processes, such as response preparation, encoding processes, motor execution etc. According to Luce (1986) the observed reaction times are the sum of the non-decision component and the decision component of processing, that is, $RT=DT+t_0$.

Although the diffusion model has been successfully applied to a wide range of experimental fields (van Ravenzwaaij et al., 2011) there are only few studies in which diffusion models were applied in intelligence research. Schubert et al. (2015) studied the factor structure of three elementary cognitive tasks that are associated with intelligence by testing 40 adults between 18 and 75 years. They showed that there is a general neurocognitive speed factor across different tasks and different levels of measurement that is associated with general intelligence. Ratcliff et al. (2011) tested three different age groups (18–25, 60–74, 75– 90 years) on different categorization tasks. They found correlations ranging .36-.90 for the three age groups between a latent drift rate factor and intelligence, whereas they reported no consistent association between the other diffusion model parameters and intelligence. They also obtained similar findings in another study, where participants' drift rate in recognition tasks was the only diffusion model parameter consistently correlated with intelligence (Ratcliff et al. 2010).

In the present study the participant has to decide quickly between two choices across all three ECTs. For instance, in the IT task, participants have to decide whether the left or right vertical line of the Greek letter pi (Π) is longer. The inspection time is thought to reflect a basic information processing ability to inspect data in the sensory register (Grudnick & Kranzler, 2001), others suggested that inspection time is a measure of the quality of stimulus representation, which reflects a post sensory level (Burns et al., 1998). Provided that inspection time is defined in reference to a criterial level of accuracy (e.g., 85%) with no discrimination between decision and non-decision components, there are two ways to model data by a diffusion model: By applying no response boundaries as applied by van Ravenzwaaij et al. (2011) or by using reaction times on the IT task. In this study we opted for reaction times. Thus, we modeled the IT data as in the other two tasks, the Posner and Go/no-go, this method enabled us to utilize the parameters of the diffusion models thereby enhancing our understanding of the speed factor and its relation with the IQ.

The present study explored the putative mediational effects of attention on the IT-IQ relation by applying the diffusion model on reaction time distributions. We tested three hypotheses: First, we examined if diffusion model parameters of the IT task predict the IT-IQ relation. We predicted that expressing the IT-IQ relation in terms of diffusion model parameters may be used interchangeably with raw inspection times. Second, we examined the functional level addressed by IT (i.e., low-level perceptual processes or higher-level cognitive processes such as attentiveness). We predicted that expressing reaction times on ECTs in terms of drift rate allows decomposing reaction times on the IT in these two underlying processes involved, namely (i) visualization speed (i.e., sensory processes) accumulating information feeding and (ii) attentional control processes which are goal-directed decisional processes related to executive skills. Third, we expected that individual differences in verbal and nonverbal intelligence are predicted by both speed of processing factors, namely low-level visualization processes and high-level attentional control processes.

Methods

Participants

The sample included 157 participants (79 females), from 7 to 18 years of age, attending elementary, junior, and senior secondary school in Cyprus. The majority of them came from middle-class families. The participants were about evenly distributed across eleven school grades and sex.

Measures

Intelligence was assessed by a Greek adaptation (Spanoudis & Tourva, 2012) of the Wechsler Abbreviated Scale of Intelligence (WASI, Wechsler, 1999). The WASI consists of four subtests: Vocabulary and Similarities to stand for verbal intelligence and Block Design and Matrix Reasoning to stand for nonverbal intelligence. Raw scores were used in the analysis. Cronbach's alphas ranged between .73 and .87 indicating that all four measures were reliable.

Three elementary cognitive tasks (ECTs) were given, namely, the IT task, the Go/no-go task, and the Posner task. All elementary tasks were delivered on a computer. E-prime 2.0 (Psychology Software Tools) data collection and analysis software was used. Tasks were presented on a Viewsonic 22-inch monitor with a 60 Hertz refresh rate. Screen resolution was set at 1600 x 900 pixels. Children sat at approximately 60 cm from the screen.

The visual inspection time task provides an index of sensory discrimination speed, and it was initially developed by Vickers et al. (1972). Administration procedures of the IT task were similar to those presented by Nettelbeck and Burns (2010). On each trial, two vertical lines differing in length and joined at the top by a horizontal line were briefly shown on the computer screen. In half of the trials, the longer line appeared on the left and in rest it appeared on right. Participant were instructed to identify the longer line by pressing the corresponding left or right key on the computer mouse. Children were instructed to respond as quickly and accurately as possible after seeing a flash mask. It is noted that the conventional instruction of the IT task emphasizes accuracy over reaction time. We instructed children to respond both accurately *and* quickly, because we planned to use reaction times for analysis by the diffusion model. Admittedly, this change in instructions may have altered the IT task, rendering more a reaction rather than an inspection time task. A flash mask (300 ms), consisting of two vertical lines shaped as lightning bolts, immediately followed the stimulus in order to prevent further stimulus processing. The stimulus duration ranged between 30 and 2000 ms, and it was altered based on an adaptive staircase algorithm (Leek, 2001) depending on the participant's performance. The initial stimulus duration was 210 ms. Inspection time estimation followed an adaptive staircase algorithm, which required four consecutive correct or incorrect responses before reducing or increasing stimulus duration by a step size of 40 ms, respectively. The program stopped after fifteen reversals of direction on the staircase or 96 trials. On each trial, the stimulus duration (time passed between stimulus onset and mask onset), accuracy, and reaction times were logged, among other variables. Adaptive staircase algorithm determined the minimal stimulus duration necessary to discriminate the longer line. The stimulus duration after completion of the 96 experimental trials or after 15 reversals was used as the measure for inspection time. Participants completed 32 practice trials before starting the main task. Two measures were obtained for each correct response: Inspection time (IT) and reaction time (ITrt).

On each trial of the Go/No-go task the picture of an animal (bear, deer, cat, cow, donkey, fox, goat, tiger, horse, mouse, pig, rabbit, zebra, sheep, and dog) appeared at the center of the screen (Durston et al. 2002). Children were instructed to press the Z key as quickly and accurately as possible any time a picture of an animal appeared ("go trials", Go condition) with the exception of the dog picture ("no-go trials"). Whenever the dog picture appeared, participant had to inhibit her response. Three blocks including 188 trials were given. In total, there were 47 no-go trials (25%) and 141 go trials. Reaction times for go trials and accuracy scores for no-go trials were collected and used.

The Posner task also measured speed of processing, and it was based on the letter-matching paradigm (Astle et al. 2012). On each trial two stimuli were simultaneously presented at the center of the screen. The stimuli were either two letters (e.g. H A) or a letter and a number (e.g. K 3). There were three blocks of 40 trials each (120 trials in total). In the first block the participant was instructed to press the Z key as quickly and accurately as possible when the stimuli were two physically identical letters (A A or a a) and the M key in all other cases (NI condition). In the second block participant was asked to press Z key as quickly and accurately as possible when the stimuli were two phonetically identical letters (A a or a a) and the M key in all other cases (PI condition). In the third block children were instructed to press the Z key as quickly and accurately as possible when the stimuli were two letters (A B or a b) and the M key in all other cases (A 4 or 2 b), This was the LI condition. Response times and accuracy were collected and used.

Cronbach's alpha for the three measures was very high (mean α=.87). Cronbach's alphas varied between .72 and .96 indicating that all of these measures were reliable.

Data analysis

Trials showing extremely fast RTs (<300 ms) or extremely slow RTs (>3000 ms) for the three ECTs were removed. To fit diffusion models to RT distributions, we used the fast-dm program developed by Voss and Voss (2015). We employed the Kolmogorov–Smirnov test statistic to estimate model parameters. The parameter z for mean starting point was set to a/2, presuming that participants had no response bias towards the correct or incorrect choices. Further, we fixed response preparation (d) and inter-trial variability (s_v) to 0, trying to make the model as parsimonious as possible. We computed three separate diffusion models one for each of the three ECTs. The parameters a, v, and to were allowed to vary freely. In the case of the Posner task drift rate was set free to differ depending on the condition, thereby estimating three values, namely, name identity (NI), physical identity (PI), and letter identity (LI).

Results

In order to test for age effects on RTs and diffusion model parameters we regrouped children into four age groups: 7-9 years, 10-12 years, 13-15 years, and 16-18 years. The mean RTs, standard deviations, and ranges of the three ECTs across the four age groups are shown in Table 1. Table 2 displays the means and standard deviations of the four more important parameters computed for the diffusion models across the four age groups. The mean percentage correct score was 82%, 94%, 93%, 90%, and 95% for the IT, PI, NI, LI, and Go variables, respectively. Model fits were acceptable for all three ECTs. Further, in all three ECTs tasks less than 5% of the models had p-values smaller than the critical p-values.

Table 1

Mean RTs, standard deviations and ranges of all reaction and inspection time measures across the four age groups

	7-9 yrs (N=41)			10-12 yrs (N=40)			13-15 yrs (N=46)			16-18 yrs (N=30)			Total (N=157)		
	M	SD	Range	M	SD	Range	M	SD	Range	M	SD	Range	M	SD	Range
IT	177	96	66-625	133	61	18-315	101	38	39-237	98	64	38-376	127	73	18-625
ITrt	576	125	353-824	435	100	279-722	399	53	297-524	415	80	285-642	454	115	279-824
Go	626	69	515-792	550	44	470-637	509	44	403-584	479	44	423-620	543	75	403-792
PI	908	214	530-1568	683	131	485-1053	641	147	416-1053	591	90	465-891	710	195	416-1568
NI	1098	280	609-1878	842	209	553-1642	751	183	505-1264	700	106	508-955	853	256	505-1878
LI	1007	309	620-2230	770	218	517-1572	725	190	407-1138	646	114	492-950	793	257	407-2230

**Note.* IT= Inspection times of the IT task, ITrt= Reaction times on the IT task, Go= Go/nogo task, PI= Physical identity condition of the Posner task, NI= Name identity condition of the Posner task, LI= Letter identity condition of the Posner task.

The mean scores, standard deviations, and ranges for all age groups across the four WASI subtests presented in Table 3. Verbal (VIQ) and Nonverbal (PIQ) IQ scores were normally distributed (skew = -0.57, kurtosis = 1.1 for VIQ and skew = -0.23, kurtosis = -0.08 for PIQ), VIQ ranged from 15 to 83 and PIQ ranged from 34 to 77.

As expected, mean RTs decreased linearly with age in all three ECTs, In the IT task, mean RTs were significantly longer in the first than the second, third, or fourth age group, $F(3, 154)= 30.31$, $p < .001$. This decreasing linear pattern was also present in inspection times of the IT task, $F(3, 154)= 11.59$, $p < .001$. In the mean RTs of the Go/no-go task each age group differed significantly from all other groups, $F(3, 154)= 62.47$, $p < .001$. The pattern in the mean RTs of the Posner task was similar (decreasing) to IT, Specifically, in the PI condition 7-9 year-olds were significantly slower than the other three age groups, $F(3, 154)= 31.16$, $p < .001$, also, the mean RTs on the NI and LI conditions were similar to the PI condition, $F(3, 154)= 27.79$, $p < .001$ and $F(3, 154)= 18.17$, $p < .001$, respectively.

Analysis of age effects on drift rates revealed a pattern similar to RTs in the opposite (increasing) direction. That is, in the IT the mean drift rate of the age group 7-9 years was significantly smaller compared to the mean drift rates of the age groups of 13-15 years, and 16-18 years, $F(3, 154)= 8.97$, $p < .001$. A similar pattern was observed in the PI condition, $F(3, 154)= 7.56$, $p < .001$, NI condition, $F(3, 154)= 6.62$, $p < .001$, and LI condition, $F(3, 154)= 5.09$, $p < .01$. In the Go/no-go mean drift rates, there were significant differences between first, second and third age groups, but not between the fourth age group and the other three, $F(3, 154)= 4.31$, $p < .01$.

To test the hypothesis that IT includes a decisional and non-decisional component, we subtracted the estimated non-decisional parameter of the diffusion model from reaction times of the IT task. If inspection time reflects only discrimination time this difference would give us a good estimate of the empirical inspection times. Indeed, no significant difference was found between inspection times and this difference, $t(155)=1.43$, $p= .15$, $r=.28$, $p< .001$.

Table 2

Means and standard deviations of the diffusion model parameters for the three ECTs across the four age groups

	7-9 years		10-12 years		13-15 years		16-18 years		Total	
	M	SD	M	SD	M	SD	M	SD	M	SD
ITv	2.40	1.08	3.01	1.12	3.72	1.50	3.93	1.90	3.26	1.52
Gov	1.45	0.96	1.48	1.33	2.40	1.80	2.24	1.91	1.90	1.59
PIv	2.37	0.67	3.33	1.03	3.41	0.93	3.42	0.76	3.13	0.97
NIv	1.56	0.45	2.13	0.78	2.34	0.91	2.48	0.88	2.11	0.84
LIv	1.92	0.81	2.55	0.64	2.57	1.19	3.18	0.78	2.51	0.99
ITα	1.03	0.22	0.90	0.21	0.85	0.20	0.84	0.21	0.91	0.22
Goα	0.64	0.34	0.59	0.27	0.77	0.31	0.73	0.32	0.68	0.32
PIα	1.53	0.38	1.23	0.29	1.25	0.35	1.16	0.24	1.30	0.35
NIα	1.48	0.38	1.23	0.28	1.28	0.42	1.12	0.22	1.29	0.36
LIα	1.68	0.37	1.38	0.32	1.44	0.42	1.38	0.36	1.47	0.39
ITz	0.50	0.13	0.48	0.12	0.52	0.10	0.52	0.13	0.51	0.12
Goz	0.22	0.17	0.26	0.22	0.28	0.14	0.28	0.18	0.26	0.18
PIz	0.56	0.09	0.58	0.10	0.61	0.09	0.66	0.06	0.60	0.09
NIz	0.51	0.10	0.51	0.11	0.54	0.11	0.54	0.11	0.52	0.11
LIz	0.57	0.08	0.56	0.10	0.60	0.09	0.60	0.08	0.58	0.09
ITt_o	0.33	0.10	0.32	0.11	0.33	0.10	0.32	0.09	0.33	0.10
Got_o	0.44	0.05	0.41	0.04	0.37	0.03	0.35	0.03	0.39	0.05
PIt_o	0.65	0.11	0.53	0.07	0.48	0.07	0.48	0.08	0.53	0.11
NIt_o	0.73	0.14	0.59	0.10	0.53	0.10	0.52	0.08	0.60	0.13
LIt_o	0.69	0.11	0.57	0.07	0.51	0.09	0.49	0.08	0.57	0.12

**Note.* The following subscriptions demarcate the diffusion model parameters of the three relevant ECTs, v= drift rate, α= boundary separation, z=starting point, t_o= non-decisional time constant.

Table 3

Means, standard deviations, and ranges for WASI subtests across the four age groups

	7-9 years			10-12 years			13-15 years			16-18 years			Total		
	M	SD	Range	M	SD	Range	M	SD	Range	M	SD	Range	M	SD	Range
Voc	32.29	6.34	16-44	42.03	6.02	25-52	47.92	7.64	29-64	53.47	8.96	33-72	43.45	10.45	16-72
Sim	22.88	5.14	12-33	28.28	5.29	15-40	33.88	5.64	16-44	35.87	5.49	25-45	30.01	7.32	12-45
BD	15.61	8.56	5-38	30.83	12.67	7-52	40.40	14.86	7-68	46.20	15.76	14-70	32.69	17.28	5-70
MR	20.80	5.33	8-29	25.28	3.27	16-31	26.77	3.53	14-33	27.87	4.22	18-33	25.06	4.89	8-33
VIQ*	55.91	8.10	34-68	52.99	7.38	35-65	55.09	11.92	15-78	55.32	12.73	26-82	54.82	10.17	15-83
PIQ*	54.33	7.10	42-77	56.05	7.90	41-72	53.90	8.29	35-69	53.63	9.97	35-66	54.50	8.23	34-77
FIQ*	110.24	12.62	79-134	109.04	12.51	80-130	108.99	18.86	51-142	108.95	20.54	66-148	109.32	16.20	51-148

**Note.* Voc= Vocabulary, Sim= Similarities, BD= Block design, MR= Matrix reasoning, * t-scores.

Correlational analysis

Table 4 shows the correlations between intelligence scores, IT, diffusion parameters of the three elementary tasks, and age. The correlation matrix between reaction times of all measures can be seen in 'Supplementary Tables'. The correlation between drift rate of the IT with reaction time on the IT was significant (-.23), as well as with VIQ, (-.22), PIQ (-.23), and full-scale IQ (-.25) at .01 level. But on the contrary, the correlations between IT and VIQ (.07) and PIQ (.04) were not significant. Significant was also the correlation between IT and drift rate of the IT (-.49), as well as between IT and reaction time of the IT task (.50). Based on these correlations we computed three structural equation models in order to test the putative mediational effects of attentional control to individual differences in intelligence scores.

Table 4

Correlations between intelligence subtests, IT, diffusion parameters of the ECTs, and age.

	1	2	3	4	5	6	7	8	9	10	11
1. Voc	1										
2. Sim	.88**	1									
3. BD	.72**	.73**	1								
4. MR	.71**	.70**	.72**	1							
5. IT	-.26**	-.28**	-.29**	-.25**	1						
6. ITv	.16*	.12	.15	.02	-.49**	1					
7. Gov	.14	.13	.03	-.06	-.14	.50**	1				
8. PIv	.41**	.34**	.43**	.37**	-.28**	.30**	.12	1			
9. NIv	.43**	.44**	.39**	.36**	-.10	.10	.15	.37**	1		
10. LIv	.40**	.36**	.31**	.24**	-.23**	.25**	.07	.41**	.41**	1	
11. Age	.75**	.70**	.66**	.55**	-.41**	.37**	.22**	.41**	.38**	.41**	1

**Note*: Voc= Vocabulary test, Sim= Similarities test, BD= Block Design test, MR= Matrix reasoning test, IT=inspection times, ITv= drift rate of the IT, Gov= drift rate of the Go/no-go task, PIv= drift rate of the Physical Identity condition, NIv= drift rate of the Name Identity condition, LIv= drift rate of the Letter Identity condition. ** $p< .05$, ** $p< .01$.

Mediational effects of attentional control (AC)

Three alternative models were evaluated using the drift rate scores for the three ECTs, age (in months), and the raw scores of the four subscales of the WASI test. The first model was a cascade model proposed by Fry and Hale (1996) assuming that there is a sequence of processing stages in which the effectiveness of processing moves from the first more influential stage to the next. According to this model, causal effects move from age to elementary processes to intelligence. This model was confirmed by Kail (2007) and Nettelbeck and Burns (2010). Here we tested a similar cascade model in which speed of visual discrimination (VS) was regressed on age, control representations held in memory (AC) was regressed on VS, and intelligence was regressed on AC. The second and third models were nested to each other and differed with respect to the effect of age on attentional control factor. More specifically, the second model (see Figure 1) investigated the possible mediation effects of attentional control on verbal and nonverbal intelligence. The third model obtained by fixing the loading of age on attentional control in an attempt to examine the influences of age on the relation between visualization speed and attentional control. All models included four latent factors: verbal intelligence, nonverbal intelligence, visualization speed, and attentional control. These models were tested to examine the effect of age, speed of processing, and attentional control on intelligence using Mplus 7.31 (Muthén & Muthén, 2015; maximum likelihood estimation was adopted). Model fit was evaluated by a variety of indexes which reflect different facets of model fit. The χ^2 statistic, Comparative fit index (CFI), Tucker Lewis index (TLI), and the root-mean-square error of approximation (RMSEA) were selected to evaluate the absolute fit of models. To compare non-nested models (model 1 vs. model 2 and 3) we employed Akaike information criterion (AIC). The AIC provides a means of ranking models and choosing the one with the smallest AIC. For comparing the fit of the two nested models we used the difference between their chi-square test statistics. To test mediation effects, we adopted the procedure described by Lau and Cheung (2012). The procedure allows to produce a bias-corrected (BC) bootstrap confidence intervals for testing mediation effects in complex latent variable models. The fit of the first model, although acceptable, was lower than optimum, χ^2 (29) = 64.86, p < .01, CFI = .96, TLI = .93, RMSEA = .09, CI_{90} = [.06, .12], and AIC = 7605.35. The fit of the second model was very high, χ^2 (26) = 42.13, p = .02, CFI = .98, TLI = .97, RMSEA = .06, CI_{90} = [.02, .09], and AIC = 7588.53. Figure 1 depicts this model. All paths from age to visualization speed, attentional control, verbal, and nonverbal intelligence were statistically significant. Moreover, the paths from visualization speed and attentional control to the intelligence factors were statistically significant. Interestingly, the regression of visualization speed on attention did not reach significance (.17, p=.13). This may be due to a significant effect of age on both, VS and AC or to our relatively limited sample size.

To test further the extent to which attentional control mediates the relation between visualization speed and verbal and nonverbal intelligence, first, we used the BC bootstrap confidence interval method and, second, we fixed the path from age to attentional control at zero. The BC bootstrap confidence interval method showed that the 95% BC confidence interval for the indirect effect VS-AC-VIQ does not contain zero (lower 2.5% limit = -3.90, upper 2.5% limit = -0.43), which indicates that the mediation effect is significantly different from zero. Likewise, the 95% BC confidence interval for the mediation effect VS-AC-PIQ does not contain zero (lower 2.5% limit = -8.10, upper 2.5% limit = -0.27). The procedure described by Lau and Cheung (2012) allows also to compare the strengths of two mediational paths in a latent variable model. Here we tested: a) the difference between the direct effect from VS to VIQ and the mediation effect from VS through AC to VIQ, b) the difference between the direct effect from VS to PIQ and the mediation effect from VS through AC to PIQ, and c) the difference between two mediation effects, that is, VS-AC-VIQ vs. VS-AC-PIQ. The confidence interval for the first difference was between 0.028 and 0.105, suggesting that the mediation effect VS-AC-VIQ is significantly different from the direct effect VS-VIQ. The confidence interval for the second difference is between 0.047 and 0.189, which does not contain zero. Hence, the mediation effect VS-AC-PIQ is significantly larger than the direct effect from VS to PIQ. Similarly, the BC confidence interval for the third difference is between 0.172 and 1.787, which does not contain zero. Therefore, we conclude that the mediation effect VS-AC-PIQ is significantly larger than the mediation effect VS-AC-VIQ. The fit of the third model was also acceptable, χ^2 (27) = 66.89, p < .01, CFI = .95, TLI = .92, RMSEA = .09, CI_{90} = [.07, .13], and AIC = 7611.28. By comparing the two nested models (model 2 against model 3) we conclude that age moderates the relation between VS and AC, $\Delta\chi^2(1)$ = 24.76, p < .001. After fixing the path from age to AC at zero, the loading of VS on AC becomes significant (.57, p<.01), whereas the coefficients of paths from VS to VIQ and PIQ increase (-.34 and -.56, respectively). Figure 1 illustrates that verbal and nonverbal intelligence are predicted significantly by visualization speed and attentional control factors which, in turn, are influenced by age.

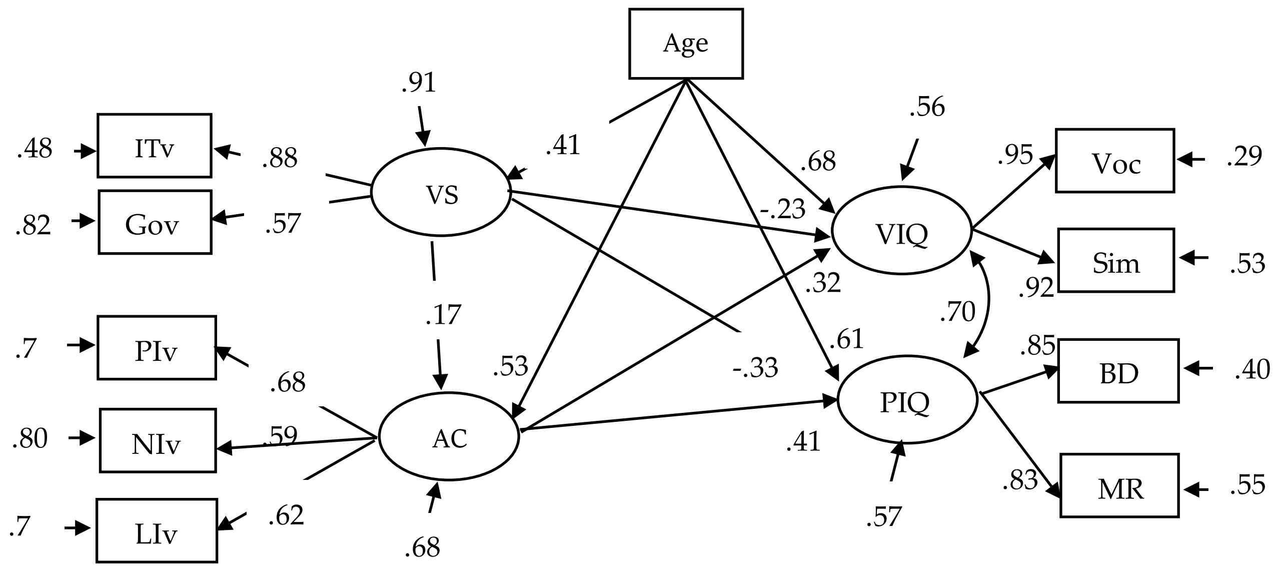

Figure 1. Structure of the model representing the relations of the parameters of the diffusion models with VIQ and PIQ

Note. VS= Visualization Speed, AC= Attentional Control, VIQ= Verbal IQ, PIQ= Nonverbal IQ, ITv= drift rate of the IT, PIv= drift rate of the Physical Identity condition, NIv= drift rate of the Name Identity condition, LIv= drift rate of the Letter Identity condition, Gov= drift rate of the Go/no-go task.

Discussion

This study aimed to explore the putative mediational effects of attentional capacity on the IT-IQ association using diffusion model analysis. For this purpose, we estimated diffusion models which revealed that drift rates of the three ECTs accounted for 69.5% of the variance in verbal intelligence and 66.3% of the variance in nonverbal intelligence. About half of this variance (17%) is related to a visualization speed factor comprised of drift rates of IT and Go/no-go measures. The 42.3% of the variance in verbal and nonverbal intelligence is related to goal-directed aspects of cognitive functioning including the three measures extracted from the Posner task.

Therefore, first, the results (see Tables 1, 2, 4, 5) show that diffusion model parameters can be used to study ECTs-IQ relations. Drift rates tended to increase and boundary separation and non-decision parameters tended to be rather stable across the three ECTs regardless of information-processing demands within each task. Drift rates of all experimental tasks showed a linear increase across the three ECTs. Notably, the other diffusion model parameters were invariant. This finding is in line with the studies that reported data using the diffusion model (Schubert et al., 2016). We have shown that the drift rate parameter can be considered as a reliable index of speed of processing across different tasks. Our findings support the conclusion of Schubert et al. (2016) that diffusion model analysis provides a promising avenue for shedding light on the mechanism underlying the relationship of elementary cognitive processes with individual differences in intelligence.

Moreover, our results suggest that within the framework of diffusion models, tasks such as the Go/no-go measure are examples of two-choice tasks in which one response is associated with one decision boundary and the other response is associated with the other decision boundary. The moderate correlation (.50) between the drift rates of Go/no-go task with IT may be interpreted as evidence that the decision to respond (left or right vertical line) seems to be associated with an implicit choice (at an implicit decision boundary).

Regarding our second hypothesis, there are several implications of these findings for a theory relating ECTs, IT in particular, with individual differences in IQ. First, the IT task measures aspects of mental processing were strongly associated with IQ. It appears that two processes play a major role when performing an IT task: Discrimination speed and attentional control processes. This study showed that each of these processes contributes uniquely to verbal and nonverbal intelligence and to individual differences in general intelligence. These findings are in line with the results of many studies (Hutton et al., 1997) showing that IT involves both sensory and high-level goal-directed processes. Our data confirm also previous findings that IT is related more to PIQ rather than to VIQ (Grudnick & Kranzler, 2001). Our findings align with the notion that IT is a measure of a general speed factor, which includes speed of visualisation processes directly, they also align with research on the psychophysics of IT (O'Connor & Burns, 2003). Additionally, this study suggested that age strengthens attentional control abilities which in turn strengthen intelligence. Therefore, increases in intelligence may be related to a broader ability to impose top-down attentional control, resulting in a superior ability to direct attention to task-relevant aspects of target stimuli. Demetriou et al. (2014) showed that the development of executive processes is directly related to awareness and regulation of cognitive processes, this relation changes with age, and it is related to changes in fluid intelligence. Therefore, further research is needed that would focus on age-specific and task-specific associations with intelligence throughout childhood and adolescence including independent measures of mental processes underlying attentional control and mental self-management.

The negative values of path coefficients from visualization speed to verbal and nonverbal intelligence require special mention. Based on the diffusion model theory we expected to find positive correlation between the drift rate of speed of processing measures and intelligence scores. Indeed, Schmiedek et al. (2007) and Schubert et al. (2016) reported positive correlation between reasoning ability or general intelligence factors and drift rate factors derived from reaction time tasks. However, both studies included adult participants. The present study included children ranging in age from 7-18 years. The negative correlation between visualization speed and intelligence scores may be taken as an indication that smarter individuals have a slower rate of information uptake as reflected in the drift rate parameter. Alternatively, negative correlations may reflect the fact that performance on processing speed and attention control levels off at about the age of 13 years (Demetriou et al., 2012) while reasoning underlying performance on the WASI continues to develop. This pattern of relations is known to yield negative correlations (Shrout & Bolger, 2002).

Table 4 shows that there is a strong positive correlation between age and drift rate in IT. To test a possible suppression effect of age on the relation of visualization speed with intelligence scores we refined model 2 by fixing all the paths of age on VS, AC, VIQ, and PIQ. The fit statistics and model parameters of the computed model were χ^2 (30) = 207.80, p < .01, CFI = .79, TLI = .69, RMSEA = .19, CI_{90} = [.17, .22], suggesting that age has a suppressing effect on the relation of drift rate with intelligence scores. This result is an agreement with the interpretation above and suggests that findings about drift rate parameter-age relations must be taken with caution. It also illustrates the need for more research on the relationship between diffusion model parameters and intelligence in school age and adolescence.

Conclusions

In conclusion, the results indicate that inspection time improves throughout the age range of 7 to 18 years, it is related to intelligence from early school age through young adulthood, it uniquely contributes to individual differences in intelligence, also, it reflects top-down sensory and attentional control processes underlying the IT-IQ relationship, finally, individual differences in drift rate of ECTs predict significantly individual differences in intelligence. However, simple this measure appears, it seems to come at the cross-road of bottom-up and top-down processes which may relate to the grasp of self-awareness and self-control. However, this is obviously a question for further study.

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Appendix

Table 5

Correlations between intelligence subtasks, inspection time, reaction times of the ECTs, and age

	1	2	3	4	5	6	7	8	9	10	11
1. Voc	1										
2. Sim	.88**	1									
3. BD	.72**	.73**	1								
4. MR	.71**	.70**	.72**	*1*							
5. IT	-.26**	-.28**	-.29**	-.25**	1						
6. ITrt	-.42**	-.40**	-.43**	-.43**	.50**	1					
7. Go	-.59**	-.60**	-.61**	-.51**	.47**	.61**	1				
8. PI	-.56**	-.51**	-.51**	-.45**	.36**	.47**	.68**	1			
9. NI	-.59**	-.58**	-.52**	-.48**	.40**	.47**	.67**	.88**	1		
10. LI	-.53**	-.53**	-.44**	-.41**	.33**	.36**	.55**	.84**	.85**	1	
11. Age	.75**	.70**	.66**	.55**	-.41**	-.51**	-.72**	-.60**	-.61**	-.52**	1

**Note.* Voc= Vocabulary test, Sim= Similarities test, BD= Block Design test, MR= Matrix reasoning test, IT= Inspection times of the IT task, ITrt= Reaction times on the IT task, Go= Go/nogo task, PI= Physical identity condition of the Posner task, NI= Name identity condition of the Posner task, LI= Letter identity condition of the Posner task, ** p< .05, ** p< .01.

ΕΜΠΕΙΡΙΚΗ ΕΡΓΑΣΙΑ | RESEARCH PAPER

Διερευνώντας τη σχέση της μέτρησης του χρόνου οπτικής επιθεώρησης και της νοημοσύνης σε παιδιά και εφήβους

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Νοημοσύνη,
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ΠΕΡΙΛΗΨΗ

Η μέτρηση του χρόνου οπτικής επιθεώρησης (ΜΧΟΕ) συνιστά δείκτη ατομικών διαφορών στην ταχύτητα αντιληπτικής διάκρισης. Είναι μια αξιόπιστη προβλεπτική μέτρηση της νοημοσύνης. Ωστόσο, οι λόγοι που καθορίζουν τη σχέση μεταξύ της ΜΧΟΕ και της νοημοσύνης δεν είναι σαφείς, καθώς λίγες μελέτες διερεύνησαν τους παράγοντες που υπόκεινται αυτής της σχέσης. Η παρούσα μελέτη εξέτασε πώς η επίδοση σε μια τροποποιημένη εκδοχή της μέτρησης του χρόνου οπτικής επιθεώρησης σχετίζεται με τις ατομικές διαφορές στον έλεγχο της προσοχής και πώς αυτή η σχέση επηρεάζεται από την ηλικία. Συνολικά 157 παιδιά από 7 έως 18 ετών εξετάστηκαν σε μια μέτρηση χρόνου οπτικής επιθεώρησης, μια μέτρηση χρόνου αντίδρασης Προχώρα/Σταμάτα, μια μέτρηση αντιστοίχισης γραμμάτων και τη συντομευμένη κλίμακα νοημοσύνης Wechsler (WASI). Η μοντελοποίηση διάχυσης έδειξε ότι η ΜΧΟΕ συλλαμβάνει τις διαδικασίες αντίληψης και προσοχής από πάνω προς τα κάτω που διέπουν τη σχέση ΜΧΟΕ-Πηλίκου Νοημοσύνης και ότι οι ατομικές διαφορές στο ρυθμό έκπτωσης των βασικών γνωστικών μετρήσεων προβλέπουν τις ατομικές διαφορές στη νοημοσύνη. Επομένως, η ΜΧΟΕ και η προσοχή συνεισφέρουν σημαντικά στην πρόβλεψη της μεταβλητότητας του Πηλίκου Νοημοσύνης.