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MOST intelligent people are accurate and SOME fast people are intelligent. Intelligence, working memory, and semantic processing of quantifiers from a computational perspective

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ABSTRACT

The paper explores the relationship between intelligence and the semantic processing of natural language quantifiers. The first study revealed that intelligence is positively associated with the subjects' performance when solving a picture verification task with one of the four types of sentences: Aristotelian (e.g. 'All cars are red'), parity (e.g. 'An even number of cars are red'), numerical (e.g. 'More than five cars are red'), and proportional ('More than half of the cars are red'). The strongest relationship was observed between the cognitive ability and the accuracy of proportional sentences, in accordance with the computational theory which predicts the highest engagement of working memory (WM) within the group of proportional quantifiers. Moreover, individuals with higher intelligence reacted faster, but this was observed only in case of quantifiers with low complexity. Exploring further, in the second study we found that WM and intelligence were both significant predictors of subjects' score on proportional sentences. In the third study, we examined the relationships between quantifiers, intelligence, short-term memory (STM), and executive control function. STM was correlated with all types of quantifiers that need counting and keeping track of elements (parity, numerical, and proportional). Only proportional quantifiers were associated with cognitive control. The obtained results are discussed within the computational paradigm of language processing.

1. Introduction

Verbal comprehension is regarded as one of the basic cognitive processes underlying general intelligence (Sternberg, 1977). In the context of information processing approach to intelligence, usually Clark and Chase's (1972) theory has been taken as an illustrative example of verbal functioning (Hunt & McLeod, 1978; Sternberg, 1977). This concept describes a major process in language comprehension, namely deciding whether a linguistic statement truly describes one's observations about the world. Clark and Chase (1972) have studied this problem using the sentence–picture verification paradigm in which subjects verified simple propositions, e.g., "Star is above plus", "Plus is not above star", against simple pictures presenting a plus placed below a star or vice versa. Clark and Chase (1972) have proposed the comparison model, according to which both a sentence and a picture are encoded in positive elementary propositional form and then compared in the verification process. Sentence encoding, picture encoding, comparing, and responding are four serially ordered stages, and their component latencies are additive. The comparison between sentence and picture is facilitated if the corresponding

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elements match and takes longer if they mismatch. Therefore, the greater the number of mismatches the more complex the comparison process (Tanenhaus, Caroll, & Bever, 1976). MacLeod, Hunt, and Mathews (1978) found that the efficiency in the sentence–picture verification task is associated with psychometric measures of general abilities.

Although the cognitive approach to intelligence is still of significant interest, studies devoted to verbal processing within the simple semantic paradigm have been recently less popular. However, findings on the computational model of natural language quantifiers seem to be promising (McMillan, Clark, Moore, Devita, & Grossman, 2005; Szymanik & Zajenkowski, 2010). Quantifiers (e.g., “all”, “some”, “most”) allow us to express the number knowledge in language. For instance, we can say “All men are mortal” or “Most people are intelligent” (see, e.g., Peters & Westerståhl, 2006). The computational theory of quantifier processing was initiated by Van Benthem (1986). It associates with every quantifier a minimal abstract computational device (automata) that can compute the meaning of the quantifier sentence. It was suggested that the cognitive difficulty of quantifier processing might be assessed on the basis of the complexity of the minimal corresponding automata (Szymanik, 2007).

Szymanik (2007) proposed to distinguish four types of quantifiers, which require different automata, and potentially various cognitive functions. First, a very simple automaton is necessary to handle Aristotelian quantifiers, such as “all” or “some”. They are recognizable by finite-automata with only two states. Intuitively, to test whether “Every car is red” is true, we do not have to memorize anything. It suffices to check all given cars one by one. If we find a non-red one, then we know that the statement is false. If we check the cars and do not find any non-red cars, then the statement is true. The automaton, then, requires only two states: *accepting*, in which it stays until it finds a non-red item whereupon it turns to *rejecting*.

Numerical quantifiers are of the form, e.g., “more than n”, “fewer than n”, and the corresponding machines are also finite-automata, but this time the number of states depends on n. To verify a sentence “More than three cars are red” we need to count red cars and make sure that there are at least four.

Parity quantifiers, “an even number of”, “an odd number of”, can be also recognized by two state finite-automata, but this time the machines need to loop between the states. For example, consider the statement “An even number of the cars is red.” When you find a red car you are in a rejecting state (you can write “false” on the hypothetical blackboard), if you find another one you switch to an accepting state (you erase “false” and put “true”), then if you see another red car you switch to rejecting state again (put “false” in place of “true”), and so on. At every moment you have only one digit on the blackboard no matter how big the set of cars. A two state finite automaton can realize such algorithm.

Finally, the most complex are proportional quantifiers (“less than half”' or “more than half”), which require a recognition mechanism with unbounded internal memory (Van Benthem, 1986). During the computation of these sentences, the sizes of two sets need to be compared and that cannot be simulated by a finite-automata but a push-down automata (PDA), which contain a stack—a form of storage system. For instance, in order to verify the sentence “More than half of the cars are red”, one has to count and hold in the short-term memory the number of red cars and then compare this with the total number of cars. No such memorization/comparison is necessary when processing other quantifiers.

The presented model was tested in a series of empirical studies assessing how people process various quantifier sentences with respect to their computational complexity (Szymanik & Zajenkowski, 2009, 2010, 2011). It has been claimed that in terms of difficulty (reaction time and accuracy) the easiest are Aristotelian quantifiers. Numerical depends on the number, which determines how many counting states are necessary. Probably, the same is true about the parity quantifiers; their difficulty is related to the number of objects that one has to count in the picture. Finally, proportional quantifiers are the hardest to verify and engage working memory to the highest degree.

Actually, there is additional empirical evidence implicating WM in the verification process of proportional sentences. For instance, neuroimaging studies showed that all quantifiers activate regions of the brain responsible for number knowledge, but proportional statements engage extra brain structures specific for working memory (McMillan et al., 2005). Furthermore, Zajenkowski, Styła, and Szymanik (2011) studied a clinical group, and showed that the proportional sentence verification of patients with schizophrenia was substantially poorer than that of healthy controls. This is consistent with many recent results indicating working memory impairments causing verbal deficits in schizophrenia. Based on experiments where subjects verified sentences with quantifiers while holding arbitrary information in memory, Szymanik and Zajenkowski (2011) have suggested that an executive aspect of WM rather than storage might be crucial for processing this type of quantifiers. Maintaining irrelevant data resulted in decreased performance but only on proportional statements. The hypothesis has been more directly confirmed in a recent study where Zajenkowski, Szymanik, and Garraffa (under review) found that the accuracy of proportional sentences is strongly correlated with cognitive control.

There are theoretical as well as empirical reasons to link general intelligence with the efficiency of quantifiers processing. Theoretically speaking, quantifiers corresponding to push-down automata are more difficult to verify than quantifiers corresponding to finite-automata. This points toward an emerging view in cognitive science that the computational complexity of the cognitive task may be a good predictor of its cognitive difficulty (e.g. Szymanik, 2010). On the other hand, it was found that the increases in cognitive complexity might be related to general intelligence (Nęcka & Orzechowski, 2005; Primi, 2000; Stankov, 2000).

Empirical studies conducted so far, seem to be in agreement with theoretical assumptions. Particularly, it was found that various psychological functions are involved in quantifier verification. Aristotelian, numerical, and parity quantifiers require mainly objects counting and discriminating (Troiani, Peelle, Vesely, Clark, & Grossman, 2008), while proportional quantifiers engage working memory to a high degree (Szymanik & Zajenkowski, 2011). Since intelligence is an important predictor of many basic cognitive tasks, we predicted that it would be positively related to performance of all types of quantifiers. However, the strongest relationship should be observed between general intelligence and proportional quantifiers, because the former is strongly related to WM (e.g. Colom, Rebollo, Palacios, Juan-Espinosa, & Kyllonen, 2004). The present studies tested how intelligence as a single variable as well as taken jointly together with WM and WM-related functions is associated with each quantifier type.

2. Study 1

In the first study we tested the simple relationship between intelligence and performance of quantifiers. In a sentence–picture verification task, we measured subjects' performance on four types of sentences: Aristotelian, parity, numerical, and proportional. We hypothesized that the intelligence test score should be positively associated with accuracy on all four linguistic conditions. However, the strongest relationship should be observed between ability level and proportional sentences performance. The latter, in comparison with Aristotelian, parity, and numerical, require additional cognitive resources related to storage and integration/comparison of two numbers. As has been shown previously (Szymanik & Zajenkowski, 2011; Zajenkowski et al., under review), these processes are linked to WM. As regards reaction time, it is more difficult to characterize clear predictions. In some studies, it was found that individuals who took more time, verified proportional quantifiers more precisely in comparison with people who were faster (Zajenkowski, in press). On the other hand, a huge body of research shows that high intelligence is linked to faster responses especially in elementary tasks, such as simple or choice reaction time tasks (Jensen, 2006). It is possible that, with respect to reaction times, intelligence should be in a stronger relationship with cognitively less demanding statements, such as Aristotelian, numerical, and parity sentences than with proportional quantifiers.

2.1. Method

2.1.1. Participants

A total of 220 subjects took part in the study (127 females and 93 males). Their mean age was 22.30 ($SD = 3.10$). The sample was composed of undergraduate students from the University of Warsaw.

2.1.2. Measures and procedure

At first, participants were presented the computerized sentence–picture verification task. It consisted of 32 grammatically simple propositions in Polish containing a quantifier that referred to the color of a car on display. Color pictures of a car park with cars in it accompanied the propositions (see Fig. 1). Each picture contained 15 objects in one or two colors and was presented simultaneously with a proposition containing a quantifier, e.g. “More than half of the cars are red”. Debriefing following the experiment revealed that none of the participants had been aware that each picture consisted of exactly fifteen objects.

Eight different quantifiers were presented to each subject in four trials. The quantifiers were divided into four groups: Aristotelian quantifiers (“all”, “some”), parity quantifiers (“odd”, “even”), numerical quantifiers of high rank (“more than seven”, “fewer than eight”), and proportional quantifiers (“more than half”, “fewer than half”). Hence, in each quantifier group only

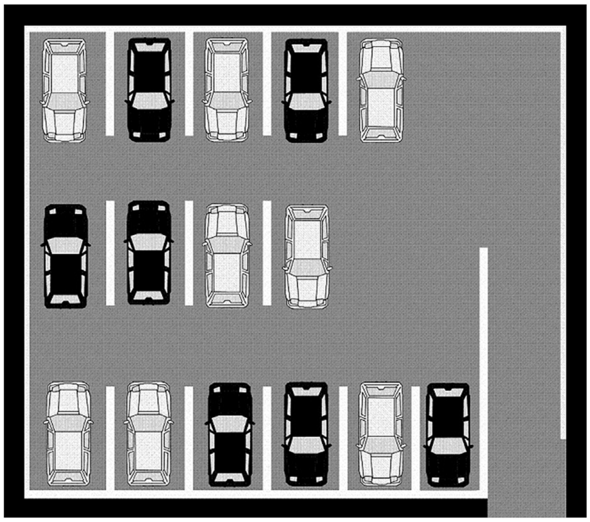

Fig. 1. An example of a picture used in study 1.

two examples of quantifiers were presented. Half of the number of each type of item was true. Subjects were asked to decide whether or not the proposition accurately describes the picture. Within each quantifier group two indexes were analyzed. First, we used median reaction time (RT) as an index of processing speed. As was noticed by Jensen (2006), median RT, unlike mean RT, is hardly affected by outliers, so that, when the number of trials is relatively small (like in our case), RT median is a more reliable measure of central tendency. Second, response accuracy understood as the total number of correct responses within four linguistic conditions was analyzed.

Afterwards, subjects were given Raven's Advanced Progressive Matrices Test (APM) (Raven, Court, & Raven, 1983), the paper-and-pencil test of fluid intelligence. It consists of 36 items that include a three-by-three matrix of figural patterns which is missing the bottom-left pattern, and eight response options which potentially match a missing one. The score was the total number of correct responses.

2.2. Results

Table 1 presents the descriptive statistics of all variables and correlations between RTs, accuracy, and the APM score. First, the differences in mean RTs and accuracy were tested to check the difficulty of quantifier groups. Repeated measures analysis of variance with type of quantifier (four levels) as the within-subject factor and the Greenhouse–Geiser adjustment was significant in case of time needed to verify a sentence ($F(2.4, 522.1) = 984{,}75$; $p < 0.001$; $\eta^2 = 0.82$). Pairwise comparisons among means (with Fisher's Least Significant Difference test) indicated that proportional quantifiers were the slowest, while Aristotelian quantifiers were the fastest ($p < 0.001$). Parity and numerical were moderate in terms of RT and did not differ significantly from each other. Because the accuracy rates of quantifiers showed generally high skewness and kurtosis coefficients, we decided to use a non-parametric test in this case. The Friedman test revealed

Table 1
Descriptive statistics and correlations of all variables from study 1.

	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. APM		−.27**	−.20**	−.17*	−.06	−.02	.30**	.28**	.40**
2.Arist RT			.48**	.62**	.41**	.07	−.19**	−.06	−.19**
3. Parity RT				.69**	.56**	.04	−.04	.02	−.03
4. Num RT					.59**	.12	−.12	.04	−.11
5. Prop RT						.01	.087	.21**	.02
6. Arist ACC							−.01	.21**	.11
7. Parity ACC								.25**	.32**
8. Num ACC									.37**
9. Prop ACC									
Mean (*SD*)	23.57 (5.7)	2011 (633)	5187 (1265)	5167 (1264)	7326 (2268)	7.80 (0.63)	7.05 (1.10)	7.16 (1.10)	6.32 (1.40)
Skew	−.88	1.47	.74	.62	.36	−9.50	−1.10	−1.57	−.83
Kurtosis	1.74	4.50	.85	.89	.10	112.90	.40	2.49	.55
Reliability	.85	.66	.79	.74	.85	.72	.50	.50	.51

Note APM—Advanced Progressive Matrices, Arist—Aristotelian, Num—Numerical, Prop—proportional, RT—reaction time median, ACC—accuracy. RTs are in milliseconds. Reliability = Cronbach's alpha, except for APM, where reliability was split-half (odd–even samples) correlations, adjusted with the Spearman–Brown prophecy formula.
* $p < 0.05$.
** $p < 0.01$.

that quantifiers differed significantly ($X^2(3) = 217.60$; $p < 0.001$), and pairwise comparisons showed that proportional quantifiers had the lowest mean rank (1.77), while Aristotelian quantifiers had the highest (3.30; $p < 0.001$). Parity (2.42) and numerical (2.51) judgments did not differ from one another. This pattern of results is in line with all previous investigations (Szymanik & Zajenkowski, 2010, 2011; Zajenkowski et al., 2011).

The score on the intelligence test was significantly and negatively correlated with RTs of three types of quantifiers. The highest association was observed in the case of Aristotelian quantifiers, while parity and numerical showed lower magnitudes of correlation coefficients. When it came to accuracy, the strongest relationship of APM was with proportional, followed by parity and numerical quantifiers.

Next, series of hierarchical regression analyses were conducted to test whether intelligence predicted RTs and accuracy of each linguistic condition after controlling for demographic variables. The results were consistent with correlations, showing that APM predicts processing speed of less complex sentences and accuracy of more demanding situations. Moreover, an interesting result concerned sex. We found that women processed Aristotelian, parity and numerical quantifiers faster than men, even after controlling for intelligence (Table 2).

Table 2
Results of hierarchical regression analyses with age, sex and intelligence (predictors) and quantifiers' RT and accuracy (dependent variables).

	Aristotelian		Parity		Numerical		Proportional	
	Δ R^2	β	Δ R^2	β	Δ R^2	β	Δ R^2	B
Reaction time								
Step 1	.02		.02		.03*		.01	
Age		.09		.05		.03		.04
Sex		−.10		−.14*		−.17		.03
Step 2	.10**		.05*		.03*		.00	
Age		.10		.06		.04		.04
Sex		−.13*		−.16*		−.18*		.03
APM		−.32**		−.22*		−.19*		−.06
Accuracy								
Step 1	.01		.01		.00		.01	
Age		.03		.06		−.02		.03
Sex		.09		.09		.05		.09
Step 2	.00		.10**		.08*			
Age		.03		.05		−.03	.15**	.01
Sex		.09		.11		.08		.12
APM		.00		.31**		.29**		.40**

Note APM—Advanced Progressive Matrices, RT—reaction time. RTs are in milliseconds. Sex: men = 0, women = 1.
* $p < 0.05$.
** $p < 0.01$.

2.3. Discussion

In study 1 we tested how intelligence is related to the verification of various quantifiers. As we expected, the accuracy of proportional sentences was in a strongest relationship with intelligence, while in the case of parity and numerical propositions the correlation was lower. The verification correctness of Aristotelian quantifiers was not related to ability test score, but in the case of this sentence type, we observed the strongest (negative) ability-speed association. Parity and numerical judgments demonstrated lower correlations, while proportional quantifiers did not show significant relationship of speed with intelligence. Generally, the results confirm our expectations that the level of human intellectual potential contribution to the processing of various quantifier types corresponds with the computational complexity hierarchy and cognitive difficulty.

These results are also in agreement with the findings suggesting that relationship between intelligence, RT, and accuracy may depend on the task difficulty (Nęcka & Orzechowski, 2005). For instance, Carpenter, Just, and Shell (1990) sought to identify the processes needed to attain success in Raven's test. The authors found that correct responses on difficult items take more time in comparison with easier problems. In a more recent study, Dodonova and Dodonov (2013), using more complex items than those commonly employed within the information-processing approach, but easier than those used in intelligence tests, found that accuracy–ability and speed–ability correlations change due to the increasing difficulty of the items. Generally, individuals who scored high on Raven's Advanced Progressive Matrices demonstrated a higher accuracy rate and faster performance than subjects with low score on intelligence test. Moreover, the accuracy–ability association became stronger as the item difficulty increased and the speed–ability correlations tended to decrease as the item difficulty increased. This is exactly what we have observed.

We found also that women processed Aristotelian, parity and numerical quantifiers faster than men. Studies devoted to sex differences in cognitive functioning show usually that women are on average slower than men (e.g. Der & Deary, 2006). However, the review of research on processing speed suggests that this might be true only in case of the most elementary RT tasks, such as simple-RT or choice-RT tasks (Roivainen, 2011). On the other hand, women appear to have an advantage in tasks requiring some aspects of verbal abilities, such as rapid-naming, matching letters and digits, or digit–symbol substitution (Roivainen, 2011). Majeres (2007) have shown in a number of studies, that verbal and speech-based processes mediate the female advantage on speeded tasks. This mechanism may also apply to our data. It is possible that women outperformed men in terms of RT, because the sentence–picture verification task engaged language-related abilities. Both sex differences and correlations with intelligence suggest that the processing speed was an important factor only with less complex linguistic conditions.

3. Study 2

The theory of quantifier processing and empirical results suggest that various quantifier types may engage different cognitive functions. The easiest sentences, containing Aristotelian quantifiers, require only simple discriminating, while to judge the truth-value of parity and numerical propositions it is also necessary to keep tracking and storing counted elements. The hardest are proportional sentences, because they engage all the described functions and an additional integration/comparison mechanism. To verify a proportional sentence, one should maintain the numbers of objects from two sets and then compare them. In other words, these linguistic structures require simultaneous processing and storage, which is the main characteristic of WM (e.g. Logie, 2011). In study 2, we examined how WM is related to each type of quantifier and whether performance on proportional sentences is explained by intelligence controlling for working memory.

3.1. Method

3.1.1. Participants

Ninety-eight undergraduate students from the University of Warsaw took part in study 2. There were 35 males and 63 females with mean age 22.36 (SD = 2.13).

3.1.2. Measures and procedure

First, a sentence–picture verification task with little modification in comparison with that from study 1 was presented to the subjects. Again, it consisted of 32 grammatically simple propositions containing a quantifier, but this time they referred to the color of a dot on display. Color pictures of dots (containing 15 objects) accompanied the propositions (see Fig. 2). The dots were similar in size (the differences did not exceed one pixel) and were distributed randomly at the picture. Other aspects of the task were exactly the same as in study 1.

After the sentence–picture verification test, participants solved a reading span task. Subjects had to decide whether the presented sentences were true. We used the material from Silly Sentences Task (Baddeley, Emslie, & Nimmo-Smith, 1992) containing such examples as *Lions are living*

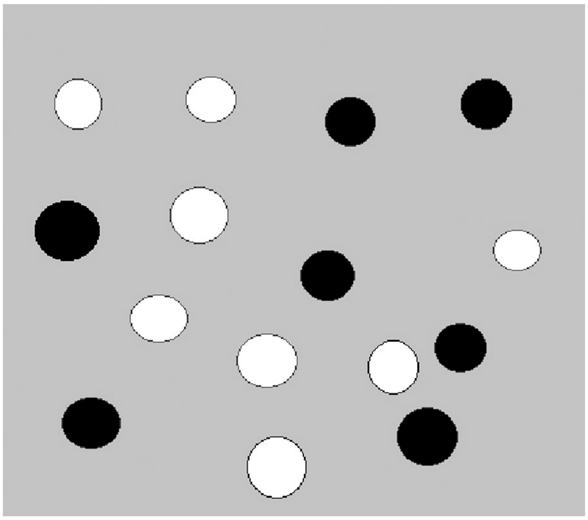

Fig. 2. An example of a picture used in study 2.

creatures, Asia is a continent, Chairs are liquid, Buses are made from apples. Additionally, they were asked to memorize the last word of each sentence for further recall. At the end of a given set, participants recalled, in their correct serial order, memorized words from the set. Set sizes ranged from 3 to 6 sentences per trial, for a total of 12 trials (4 levels × 3 trial = 12 trials total). The total score was the number of correctly recalled items from a particular set. Hence, the score might have ranged from 0 to 12.

At the end of the session, subjects were given Raven's Advanced Progressive Matrices Test.

3.2. Results

First, we tested the differences between linguistic conditions with respect to average reaction time and accuracy (see Table 3 for means and standard deviations). The analyses revealed that conditions differed significantly in case of reaction time ($F(1.9, 182.0) = 395.37$; $p < 0.001$; $\eta^2 = 0.80$) and accuracy ($X^2(3) = 86.26$; $p < 0.001$). Likewise, in study 1, pairwise comparisons indicated that proportional quantifiers were the most difficult, while Aristotelian quantifiers were the easiest in terms of RT and accuracy ($p < 0.05$). Parity and numerical quantifiers did not differ significantly from each other when it came to accuracy. However, numerical sentences took more time than parity sentences. Generally, the pattern of results is similar to that from study 1 and previous investigations (Szymanik & Zajenkowski, 2010, 2011; Zajenkowski et al., 2011).

Further, the correlations between all variables were calculated (see Table 3). Likewise, in study 1, the APM score tended to correlate negatively with RTs of Aristotelian, parity, and numerical sentences, and showed no association with proportional judgments. As regards accuracy, intelligence was significantly linked only to proportional sentences. Moreover, the APM result was strongly related to the WM task score.

Next, we conducted regression analyses to determine the unique variance in quantifiers' RT and accuracy explained by intelligence controlling for working memory. At step 1, age and sex were entered into the regression model, followed by the result from the working memory task (step 2), and the APM score (step 3; see Table 4). Most interestingly, in step 2, WM explained 12% of the variance in proportional quantifiers. Cognitive ability in step 3 accounted for an additional 9% of the variance. Moreover, when taken jointly, both predictors were significant, which may suggest that there is some unique contribution of WM and APM to the accuracy of truth-value judgments of proportional sentences. Finally, sex differences in processing speed similar to study 1 were found. However, this time women were significantly faster only in case of parity and numerical quantifiers.

3.3. Discussion

In the second study we found that the intelligence test and WM scores were associated only with the accuracy of proportional judgments. The lack of significant relationship between numerical and parity quantifiers and APM may be due to smaller sample size in this experiment in comparison with the previous one. Interestingly, in the regression model, when taken jointly, both WM and intelligence were significant, which may suggest that each of the predictors explains unique variance in proportional sentences' score. It needs to be acknowledged, however, that several factors might influence the obtained correlations. First, WM was assessed on the basis of verbal task and according to some researchers the task-specific content substantially determines the association between

Table 3
Descriptive statistics and correlations of all variables from study 2.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. APM		.41**	−.31**	−.46**	−.50**	−.22*	.05	.15	.17	.41**
2. WM			−.42**	−.33**	−.47**	−.25*	.07	.13	.12	.34**
3.Arist RT				.61**	.68**	.50**	.25*	.04	−.03	−.14
4. Parity RT					.72**	.53**	.26*	−.13	−.08	−.32**
5. Num RT						67**	.31**	.03	.04	−.28*
6. Prop RT							.31**	.06	.03	−.08
7. Arist ACC								.37**	.11	.04
8. Parity ACC									.10	.27**
9. Num ACC										.11
10. Prop ACC										
Mean (*SD*)	22.50 (6.6)	4.03 (2.10)	1895 (540)	5178 (1627)	5630 (1498)	7715 (2485)	7.88 (0.55)	7.31 (1.14)	7.08 (0.82)	6.78 (1.15)
Skew	−.63	−.11	1.22	.63	.29	.07	−7.52	2.50	−.72	−.85
Kurtosis	.36	−.87	4.40	.65	.64	−.26	64.50	7.40	.77	.75
Reliability	.83	.62	.64	.85	.81	.89	.77	.56	.49	.50

Note APM—Advanced Progressive Matrices, STM—short-term memory; Arist—Aristotelian, Num—Numerical, Prop—proportional, RT—reaction time, ACC—accuracy, RTs are in milliseconds. Reliability = Cronbach's alpha, except for APM, where reliability was split-half (odd-even samples) correlations, adjusted with the Spearman–Brown prophecy formula.

* $p < 0.05$.

** $p < 0.01$.

Table 4
Results of hierarchical regression analyses with proportional quantifiers' accuracy as dependent variable age, sex (step 1), WM (step 2) and APM (step 3) as predictors.

	Aristotelian		Parity		Numerical		Proportional	
	ΔR^2	β	ΔR^2	β	ΔR^2	β	ΔR^2	β
Reaction time								
Step 1	.05		.13**		.13*		.06	
Age		.10		.02		.06		.08
Sex		−.18		−.36**		−.34**		−.21*
Step 2	.16**		.08*		.19**		.04*	
Age		.08		.00		.04		.08
Sex		−.15		−.34**		−.31**		−.20*
WM		−.40**		−.28*		−.44**		−.20*
Step 3	.02		.11**		.10**		.01	
Age		.10		.04		.08		.09
Sex		−.13		−.29*		.−25*		−.18
WM		−.33**		−.14		−.30**		−.15
APM		−.17		−.37**		−.36**		−.13
Accuracy								
Step 1	.04		.04		.00		.00	
Age		.19		.16		.03		−.01
Sex		−.03		.15		.03		.03
Step 2	.01		.01		.01		.12*	
Age		.20		.16		.03		−.01
Sex		−.04		.14		.02		.00
WM		.08		.10		.11		.34**
Step 3	.00		.01		.02		.09*	
Age		.20		.14		.03		−.04
Sex		−.04		.13		.01		−.04
WM		.08		.04		.05		.21*
APM		.01		.13		.16		.33**

Note APM—Advanced Progressive Matrices, WM—working memory (reading span task). RTs are in milliseconds. Sex was coded 0 for men, 1 for women.
* $p < 0.05$.
** $p < 0.01$.

WM and comprehension (e.g. Daneman & Tardif, 1987). Moreover, the two tasks might have share additional amount of variance because of the fact that they both were designed in a sentence verification paradigm.

4. Study 3

Working memory is a broad construct. For instance, in a classic, multicomponent model it is described as consisting of central executive and storage subsystems (see Baddeley & Logie, 1999). Similarly, in the literature explaining the nature of intelligence–WM relationship, the role of storage function (e.g. Chuderski, Taraday, Nęcka, & Smoleń, 2012; Colom, Aba, Quiroga, Shih, & Flores-Mendoza, 2008), or cognitive control (Engle, Kane, & Tuholski, 1999) is usually emphasized (cf. Chuderski & Nęcka, 2012). Therefore, in the last study we tried to explore the contribution of WM's specific parts to quantifier comprehension. Specifically, we measured participants' short-term memory (STM) and the ability to control cognitive processes. The former may be understood as a simple storage-oriented span task with no explicit concurrent processing (see e.g. Miyake, Friedman, Rettinger, Shah, & Hegarty, 2001). As regards cognitive control, one of the most influential theories was proposed by Engle et al. (1999), who defined the attentional control as the ability to maintain mental representations in a highly active state in the presence of interference (Engle et al., 1999). Kane and Engle's (2002) review nominates as measures of controlled attention the flanker task, the antisaccade task, or the Stroop task, among others (see also Heitz & Engle, 2007).

In previous studies we found that proportional quantifiers engage cognitive control as well as short-term retention of information, while simpler linguistic structures require only storage functions (Zajenkowski et al., under review). Moreover, Szymanik and Zajenkowski (2011) observed that short-term memory is correlated with proportional judgments almost to the same degree as with other types of quantifiers. This led the authors to the conclusion that the executive aspect of WM might be responsible for the complexity of proportional quantifiers. We expected then, that this type of quantifiers should be correlated with cognitive control as well as short-term memory. Other quantifiers that require counting and storing of elements (numerical and parity) should be associated only with STM. Finally, we were interested in determining unique contribution of intelligence in the sentence-verification accuracy when controlling for both WM functions.

4.1. Method

4.1.1. Participants

There were 150 subjects in the study (96 females and 54 males). Their mean age was 22.20 (SD = 2.45). The sample was composed of undergraduate students from the University of Warsaw.

4.1.2. Materials and procedure

At the beginning participants were presented the sentence–picture verification task, which was exactly the same as that used in study 1.

The cognitive control was measured with the short version of Attention Networks Test (ANT) designed by Fan, McCandliss, Sommer, Raz, and Posner (2002). The authors' starting point was the assumption that the attentional system can be divided into three functionally and anatomically independent networks: alerting (allows maintenance of a vigilant and alert state), orienting (responsible for selection of space region to be attended), and executive control (the monitoring and resolution of conflict between expectation, stimulus, and response). In the present study we were focused on the latter network as an index of cognitive control. In the ANT task, on each trial, the participant has to decide, by pressing a button, whether a central arrow stimulus (the target) points left or right. The target is flanked by distractor stimuli, and appears above or below a central fixation point. The target stimulus may be preceded by a cue stimulus that either has a general alerting function, or indicates whether the target will appear above or below fixation. Two attributes of the task are manipulated across trials. The first is cue type, which may be absent (central fixation cross only), a central cue (asterisk), or a spatial cue (single asterisk above or below fixation cross). The second attribute is the flanker stimulus type, which may be congruent with the target (arrow points in same direction) or incongruent (arrow points in opposite direction). In each case, two flankers are presented on either side of the target. Each trial consists of the following events: (1) central fixation cross for 400–1600 ms, (2) cue or no cue for 100 ms, (3) central fixation cross for 400 ms, (4) target until participant responds, and (5) central fixation cross until total trial duration of 4000 ms has elapsed. The alerting network is calculated by subtracting the RT median of center-cue condition from the RT median of no-cue condition. The orienting index is calculated by subtracting the RT median of the spatial cue conditions from the RT median of the center cue conditions. The executive control index is calculated by subtracting the RT median of the congruent flanking conditions from the RT median of incongruent flanking conditions. In the present study we were mainly interested in the controlling network.

The last task was a computerized version of Sternberg's short-term memory measure (Sternberg, 1966). On each trial of the test, the subjects were presented with a random series of different digits, one at a time, for 300 ms, followed by a blank screen and the test digit. Participants had to decide whether the test digit had appeared in the previously displayed string. Sequences of digits of three lengths (four, six, or eight) were repeated eight times each; hence, there were 24 trials overall. The score was the total of correct responses from all conditions (range of 0 to 24).

At the end of the session participants were administered APM.

4.2. Results

First we tested whether the differences between quantifiers are similar to these obtained in studies 1 and 2 (see Table 5 for means and standard deviations). The analyses revealed that conditions differed significantly in case of reaction time ($F(2.3, 349.9) = 803.6$; $p < 0.001$; $\eta^2 = 0.84$) and accuracy ($X^2(3) = 139.60$; $p < 0.001$). Pairwise comparisons indicated that proportional quantifiers were the most difficulty, while Aristotelian quantifiers were the easiest ($p < 0.001$). Parity and numerical were at moderate level in terms of RT and accuracy and did not differ significantly from each other. This pattern of results is similar to the results from two studies reported above.

In the next step, we correlated all variables. The APM score was positively correlated with the accuracy on numerical, parity, and proportional judgments, but in the last case the magnitude was highest. It was also negatively associated with RTs of all linguistic conditions; however, the

Table 5
Descriptive statistics and correlations of all variables from study 3.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. APM		.08	−.02	−.33**	.25**	−.24**	−.23**	−.23**	−.20*	.07	.20*	.20*	.33**
2. ANT—Alerting			−.48**	−.03	.10	.10	.05	.06	.08	−.11	−.05	−.01	.14
3. ANT—Orienting				.02	.07	.03	.09	.07	.01	.04	.07	.01	−.15
4. ANT—Control					−.18*	.10	.07	.04	.03	.06	−.15	−.15	−.22**
5. STM						−.01	,01	−.06	.04	.09	.31**	.22**	.33**
6. Arist RT							.72**	.70**	.51**	−.09	−.06	−.12	−.14
7. Parity RT								.82**	.62**	.01	−.02	−.13	−.17*
8. Num RT									.62**	−.01	−.07	−.15	−.16*
9. Prop RT										−.01	.04	−.07	−.10
10. Arist ACC											.15	,16*	.10
11. Parity ACC												.30**	.18*
12. Num ACC													.22**
13. PropACC													
Mean (SD)	24.00 (5.4)	9.90 (26.72)	51.40 (30.00)	96.64 (29.75)	20.70 (2.12)	1713 (590)	4712 (1520)	4672 (1501)	7333 (2150)	7.90 (0.32)	7.30 (0.98)	7.42 (0.92)	6.60 (1.22)
Skew	−.33	−1.74	1.28	1.24	−1.00	1.34	.64	.55	.03	−6.36	−1.69	−2.15	−.70
Kurtosis	.13	15.8	8.50	3.00	1.60	3.61	.18	.42	.10	49.30	2.65	6.11	−.25
Reliability	.85	.28	.40	.77	.55	.64	.85	.82	.84	.55	.51	.49	.52

Note APM—Advanced Progressive Matrices, STM—short-term memory; Arist—Aristotelian, Num—Numerical, Prop—proportional, RT—reaction time, ACC—accuracy, RTs are in milliseconds. Reliability = Cronbach's alpha, except for APM and ANT measures, where reliabilities were split-half (odd-even for APM and random samples for ANT) correlations, adjusted with the Spearman–Brown prophecy formula.

* $p < 0.05$.

** $p < 0.01$.

lowest correlation concerned proportional sentences. These results are in line with the findings from studies 1 and 2. Moreover, APM tended to correlate with STM and control network from ANT. In the latter situation the relationship is negative, since the high result on control network indicates delay in inhibiting response to competing stimuli, and hence poor executive functioning. The STM result was positively related to accuracy of numerical, parity, and proportional quantifiers, as well as the cognitive control (negatively). Finally, the control network was also related to accuracy of judgments, but only for proportional sentences.

Further, we conducted a series of hierarchical regression analyses. In each model the accuracy and RT of judgments were dependent variable. At step 1, age and sex were entered into the regression model, followed by results from STM and cognitive control task (step 2), and the APM score (step 3; see Table 6). The analysis indicated that APM was the only significant predictor of quantifiers' processing speed in step 3. Analyzing accuracy, we found that the intelligence test score explained significantly more variance only in the case of proportional judgments. Moreover, the relationship between these judgments and cognitive control was attenuated when the APM result was added to the model. STM remained a significant predictor of all quantifiers in step 3. It is worth mentioning also, that sex differences in RT were found. Specifically, women were significantly faster in processing of numerical quantifiers.

Table 6
Results of hierarchical regression analyses with numerical, parity, and proportional quantifiers accuracy as dependent variables and age, sex (step 1), control, STM (step 2) and APM (step 3) as predictors.

	Aristotelian		Parity		Numerical		Proportional	
	Δ R^2	β	Δ R^2	β	Δ R^2	β	Δ R^2	β
Reaction time								
Step 1	.01**		.02		.02		.01	
Age		.07		.05		−.02		.02
Sex		−.06		−.13		−.13		−.05
Step 2	.01		.01		.03		.01	
Age		.08		.05		−.02		.01
Sex		−.07		−.14		−.15		−.06
Control		.12		.09		.12		−.01
STM		−.02		−.05		−.11		−.11
Step 3	.05*		.05*		.04*		.04*	
Age		.06		.03		−.04		−.01
Sex		−.09		−.16		−.17*		−.08
Control		.05		.02		.06		−.07
STM		.03		.01		−.07		−.07
APM		−.24*		−.24*		−.21*		−.21*
Accuracy								
Step 1	.01		.04		.01		.01	
Age		−.08		−.21*		−.02		−.03
Sex		−.05		−.02		.07		−.06
Step 2	.01		.10*		.07*		.13*	
Age		−.07		−.20*		−.02		−.02
Sex		−.04		−.02		.10		−.01
Control		.07		−.12		−.12		−.16*
STM		.09		.28*		.20*		.30*
Step 3	.01		.01		.02		.04*	
Age		−.07		.20*		−.02		−.02
Sex		−.03		.03		.11		.01
Control		.09		.08		−.08		−.10
STM		.08		.26*		.18*		.25*
APM		.08		.11		.15		.23*

Note APM—Advanced Progressive Matrices, STM—short-term memory (reading span task). RTs are in milliseconds. Sex: 0 for men, 1 for women.
* $p < 0.05$.
** $p < 0.01$.

4.3. Discussion

Our results showed that storage functions are correlated with all types of quantifier judgments that demand counting and keeping track of elements, namely parity, numerical, and proportional judgments. Additionally, the latter were also associated with cognitive control. When intelligence test score was entered in the regression models, STM remained significant in all analyzed linguistic conditions, but the significance of control function disappeared. This suggests that storage is a rather independent process from intellectual abilities in language comprehension. However, it is worth mentioning that the short-term memory measure required processing of quantities (digits), the function engaged also in the verification task. Previous investigations suggest that the specific experimental material may influence the STM–language relationship (e.g. Cantor, Engle, & Hamilton, 1991). In the future studies, it would be interesting to examine the associations between memory measures using a wide range of stimuli (e.g. letters, symbols, etc.) and sentence comprehension.

More complex structures also engage executive aspects of WM, which is attenuated by intelligence in a joined model. This result is in agreement with theories emphasizing that cognitive control is an important factor of WM and intelligence (e.g. Engle et al., 1999) as well as complex linguistic structures (Novick, Trueswell, & Thompson-Schill, 2005).

The results from study 3 are consistent with the distinction within the WM system made by Gibson (2000). The author suggested that there might be two types of WM costs underlying language processing: storage costs and integration costs. Gibson (2000) analyzed mainly structure dependencies between elements in a sentence that are separated by other elements. Storage costs are related to keeping track of incomplete syntactic dependencies in a sentence, while integration costs are responsible for integrating incoming words with earlier words in the sentence which need to be retrieved from memory. The latter might be especially important in object-extracted constructions in which the head noun is the object of the relative clause and is difficult to integrate with the verb (see also the general discussion below). As was argued by Zajenkowski et al. (under review), it is possible that numerical and parity judgments engage only storage costs of WM because they require keeping track of elements, while proportional quantifiers additionally involve integration costs, since to verify them one needs to retrieve from memory the cardinalities of two sets, and then compare (integrate) them. One may conclude that quantifiers differ in terms of operations or rules necessary to verify them. The increasing number of rules required to attain success in a task is named as one of the important characteristics of a task complexity and also a predictor of fluid intelligence (Nęcka & Orzechowski, 2005; Primi, 2000).

5. General discussion

We studied the contribution of intelligence in the processing of various natural language quantifiers. In the first study, we showed that the role of cognitive ability in the accuracy of judgments increases along with the computational complexity of involved quantifiers. In the second experiment, we found that intelligence and WM share some variance, but also make unique significant contribution in predicting subjects' accuracy in proportional judgments. The last study indicated that STM remains a significant predictor of numerical, parity, and proportional judgments, even after intelligence is entered in the model. Finally, proportional quantifiers are associated with cognitive control, however, this effect is attenuated in a joined model with intelligence.

Our results may be discussed in a broader context of language comprehension. Interestingly, it was shown that the contribution of intelligence and working memory to various linguistic structures depends on the syntactic complexity of the verbal material (Daneman & Merikle, 1996). The classic examples of demanding sentences are embedded structures (e.g. 'This land and these woods can be expected to rent itself and sell themselves, respectively'), described by Miller and Chomsky (1963) as grammatically correct, but difficult to understand. Other known examples are sentences containing a center-embedded object-relative clause, such as, "The doctor that the writer helped climbed the mountain." Such complex language constructions make large demands on the cognitive system because they require maintaining their parts in memory (e.g. noun phrases), while trying to integrate them with other expressions (e.g. verbs). It was shown that in a reading span task items with such complex sentences are much more prone to error than simpler examples (e.g. subject clause; see e.g. Gordon, Hendrick, & Levine, 2002). Recently, Zajenkowski et al. (under review) argued that the WM mechanism involved in the proportional judgments might be actually similar to the one necessary for the parsing of grammatically complex sentences. In particular, the parsing of embedded sentences, likewise the verification of proportional sentences, require holding in memory some parts of the sentence for further adequate integration with other expressions (e.g. Gordon et al., 2002; Miller & Chomsky, 1963). There may be also a theoretical similarity. Chomsky (1957, 1969) famously proposed a mathematical model of formal grammars to talk about the complexity of the syntactic constructions. His complexity hierarchy classifies grammatical constructions into regular, context-free, context-sensitive, and recursively enumerable. The higher the construction in the hierarchy, the more difficult it is. The computational model of quantifier verification has been formulated in terms of automata-theory that exactly corresponds to the Chomsky hierarchy: finite-automata recognize regular languages, PDAs recognize context-free languages, linear-bounded non-deterministic Turing machines correspond to the context-sensitive languages, and finally the class of enumerable languages is recognizable by Turing machines (see, e.g., Hopcroft, Motwani, & Ullman, 2006). It is possible that cognitive abilities are associated with complex structures (e.g. embedded sentences, proportional judgments) to a higher degree than with simple linguistic constructions (e.g. subject-clefts, Aristotelian, numerical, and parity judgments), due to some universal mechanism, which may be described from the computational perspective as a necessary engagement of WM.

We believe that the computational theory of quantifier processing may also be useful for a deeper understanding of human intelligence. Cognitive science has put much effort into investigating the computational level of linguistic competence and today computational restrictions are taken seriously when discussing cognitive capacities. For instance, a psychological version of the Church–Turing thesis (Church, 1936; Turing, 1936)—stating that the human mind can only deal with computable problems—is widely accepted. Moreover, complexity restrictions on cognitive tasks have already been noted in the philosophy of language and mind (see e.g. Hofstadter, 2007), the theory of language (see e.g., Szymanik, 2009), and psychology of vision (see e.g., Tsotsos, 1990), leading to many variants of the Tractable Cognition Thesis stating that human cognitive (linguistic) capacities are constrained by computational resources, like time and memory (see e.g., Van Rooij, 2008). In the present studies we reported that intelligence relationship with different quantifier judgments corresponds to the differences in the computational complexity of verification procedure. Therefore, it is possible that computational constraints described by linguists and logicians apply also to human general abilities.

If the latter statement is true, then the computational characteristics of cognitive capacities may also be seriously considered in the field of artificial intelligence, especially in the attempts to simulate human linguistic behavior. As was noted by Detterman (2011), in the past human intelligence researchers and many artificial intelligence researchers dismissed the possibility of similarity between artificial and human intelligence. However, the author argues that this view may soon change due to the recent progress in computer programming. One may speculate whether the similarities between human and artificial intelligence could be partially explained by the fact that both systems have the same computational constraints.

It should be acknowledged that several factors might limit our conclusion. First, we used only one measure of intelligence in all reported investigations. Although Raven's Progressive Matrices were constructed to capture Spearman's *g* (Raven et al., 1983), some researchers point out that it is impossible to identify g with any single test—it must be approximated by the aggregation of several highly *g*-saturated measures (Ackerman, Beier, & Boyle, 2005). To avoid the risk that our results are contaminated by intelligence test specific variance (e.g. spatial ability) more data are necessary with wider range of abilities test. The same limitation concerns WM and other cognitive tasks we used. Therefore, the present studies may be treated rather as preliminary results for further more in-depth examination of the relationship between g and quantifier comprehension.

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References

Ackerman, P. L., Beier, M. E., & Boyle, M. O. (2005). Working memory and intelligence: The same or different constructs? *Psychological Bulletin*, *131*, 30–60.

Baddeley, A. D., Emslie, H., & Nimmo-Smith, I. (1992). *The Speed and Capacity of Language Processing (SCOLP) test.* Bury St Edmunds: Thames Valley Test Company.

Baddeley, A. D., & Logie, R. H. (1999). Working memory: The multiple component model. In A. Miyake, & P. Shah (Eds.), *Models of working memory: Mechanisms of active maintenance and executive control* (pp. 28–61). New York: Cambridge University Press.

Cantor, J., Engle, R. W., & Hamilton, G. (1991). Short-term memory, working memory, and verbal abilities: How do they relate? *Intelligence*, *15*, 229–246.

Carpenter, P. A., Just, M. A., & Shell, P. (1990). What one intelligence test measures: A theoretical account of the processing in the Raven Progressive Matrices test. *Psychological Review*, *97*, 404–431.

Chomsky, N. (1957). *Syntactic structures.* The Hague/Paris: Mouton.

Chomsky, N. (1969). *Aspects of the theory of syntax.* Cambridge, MA: The MIT Press.

Chuderski, A., & Nęcka, E. (2012). The contribution of working memory to fluid reasoning: capacity, control, or both? *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *38*, 1689–1710.

Chuderski, A., Taraday, M., Nęcka, E., & Smoleń, T. (2012). Storage capacity explains fluid intelligence but executive control does not. *Intelligence*, *40*, 278–295.

Church, A. (1936). An unsolvable problem of elementary number theory. *American Journal of Mathematics*, *58*, 345–363.

Clark, H. H., & Chase, W. G. (1972). On the process of comparing sentences against pictures. *Cognitive Psychology*, *3*, 472–517.

Colom, R., Aba, F. J., Quiroga, M. A., Shih, P. C., & Flores-Mendoza, C. (2008). Working memory and intelligence are highly related constructs, but why? *Intelligence*, *36*, 584–606.

Colom, R., Rebollo, I., Palacios, A., Juan-Espinosa, M., & Kyllonen, P. C. (2004). Working memory is (almost) perfectly predicted by *g*. *Intelligence*, *32*, 277–296.

Daneman, M., & Merikle, P. M. (1996). Working memory and language comprehension: A meta-analysis. *Psychonomic Bulletin & Review*, *3*, 422–433.

Daneman, M., & Tardif, T. (1987). Working memory and reading skill re-examined. In M. Coltheart (Ed.), *Attention and performance XII: The psychology of reading* (pp. 491–508). Hove: Erlbaum.

Der, G., & Deary, I. J. (2006). Age and sex differences in reaction time in adulthood: Results from the United Kingdom Health and Lifestyle Survey. *Psychology and Aging*, *21*(1), 62–71.

Detterman, D. K. (2011). A challenge to Watson. *Intelligence*, *39*, 77–78.

Dodonova, Y., & Dodonov, Y. (2013). Faster on easy items, more accurate on difficult ones: Cognitive ability and performance on a task of varying difficulty. *Intelligence*, *41*, 1–10.

Engle, R., Kane, M., & Tuholski, S. (1999). Individual differences in working memory capacity and what they tell us about controlled attention, general fluid intelligence and functions of the prefrontal cortex. In A. Miyake, & P. Shah (Eds.), *Models of working memory: Mechanisms of active maintenance and executive control* (pp. 102–134). London: Cambridge Press.

Fan, J., McCandliss, B. D., Sommer, T., Raz, A., & Posner, M. I. (2002). Testing the efficiency and independence of attentional networks. *Journal of Cognitive Neuroscience*, *14*(3), 340–347.

Gibson, E. (2000). The dependency locality theory: A distance-based theory of linguistic complexity. In A. Marantz (Ed.), *Image, language, brain: Papers from the first mind articulation project symposium* (pp. 94–126). Cambridge, MA: MIT Press.

Gordon, P. C., Hendrick, R., & Levine, W. H. (2002). Memory load interference in syntactic processing. *Psychological Science*, *13*, 425–430.

Heitz, R. P., & Engle, R. W. (2007). Focusing the spotlight: Individual differences in visual attention control. *Journal of Experimental Psychology. General*, *136*, 217–240.

Hofstadter, D. (2007). *Goedel, Escher, Bach.* New York: Tusquets.

Hopcroft, J. E., Motwani, R., & Ullman, J. D. (2006). *Introduction to automata theory, languages, and computation.* Boston: Addison-Wesley Longman Publishing Co.

Hunt, E. B., & McLeod, C. M. (1978). The sentence-verification paradigm: A case study of two conflicting approaches to individual differences. *Intelligence*, *2*, 129–144.

Jensen, A. R. (2006). *Clocking the mind: Mental chronometry and individual differences.* Amsterdam: Elsevier.

Kane, M. J., & Engle, M. J. (2002). The role of prefrontal cortex in working-memory capacity, executive attention, and general fluid intelligence: An individual-differences perspective. *Psychonomic Bulletin & Review*, *9*, 637–671.

Logie, R. H. (2011). The functional organisation and the capacity limits of working memory. *Current Directions in Psychological Science*, *20*, 240–245.

MacLeod, C. M., Hunt, E. B., & Mathews, N. N. (1978). Individual differences in the verification of sentence–picture relationships. *Journal of Verbal Learning and Verbal Behavior*, *17*, 493–507.

Majeres, R. J. (2007). Sex differences in phonological coding: Alphabet transformation speed. *Intelligence*, *35*, 335–346.

McMillan, C., Clark, R., Moore, P., Devita, C., & Grossman, M. (2005). Neural basis for generalized quantifiers comprehension. *Neuropsychologia*, *43*, 1729–1737.

Miller, G. A., & Chomsky, N. (1963). Finitary models of language users. In D. R. Luce, R. R. Bush, & E. Galanter (Eds.), *Handbook of mathematical psychology*, *vol. II*, New York: John Wiley.

Miyake, A., Friedman, N. P., Rettinger, D. A., Shah, P., & Hegarty, M. (2001). How are visuospatial working memory, executive functioning, and spatial abilities related? A latent-variable analysis. *Journal of Experimental Psychology. General*, *130*, 621–640.

Nęcka, E., & Orzechowski, J. (2005). Higher-order cognition and intelligence. In R. Sternberg, & J. Pretz (Eds.), *Cognition and intelligence: Identifying the mechanisms of the mind* (pp. 122–141). Cambridge University Press.

Novick, J. M., Trueswell, J. C., & Thompson-Schill, S. L. (2005). Cognitive control and parsing: Reexamining the role of Broca's area in sentence comprehension. *Cognitive, Affective, & Behavioral Neuroscience*, *5*, 263–281.

Peters, S., & Westerståhl, D. (2006). *Quantifiers in language and logic.* Oxford: Oxford University Press.

Primi, R. (2000). Complexity of geometric inductive reasoning tasks: Contribution to the understanding of fluid intelligence. *Intelligence*, *30*, 41–70.

Raven, J. C., Court, J. H., & Raven, J. (1983). *Manual for Raven's Progressive Matrices and vocabulary scales (Section 4: Advanced Progressive Matrices).* London: H. K. Lewis.

Roivainen, E. (2011). Gender differences in processing speed: A review of recent research. *Learning and Individual Differences*, *21*, 145–149.

Stankov, L. (2000). Complexity, metacognition, and fluid intelligence. *Intelligence*, *28*, 121–143.

Sternberg, S. (1966). High-speed scanning in human memory. *Science*, *153*, 652–654.

Sternberg, R. (1977). *Intelligence, information processing, and analogical reasoning: The componential analysis of human abilities.* Hillsdale, NJ: Erlbaum.

Szymanik, J. (2007). A comment on a neuroimaging study of natural language quantifier comprehension. *Neuropsychologia*, *45*, 2158–2160.

Szymanik, J. (2009). *Quantifiers in TIME and SPACE. Computational complexity of generalized quantifiers in natural language.* PhD Thesis. University of Amsterdam.

Szymanik, J. (2010). Computational complexity of polyadic lifts of generalized quantifiers in natural language. *Linguistics and Philosophy*, *33*(3), 215–250.

Szymanik, J., & Zajenkowski, M. (2009). Improving methodology of quantifier comprehension experiments. *Neuropsychologia*, *47*, 2682–2683.

Szymanik, J., & Zajenkowski, M. (2010). Comprehension of simple quantifiers. Empirical evaluation of a computational model. *Cognitive Science*, *34*, 521–532.

Szymanik, J., & Zajenkowski, M. (2011). Contribution of working memory in the parity and proportional judgments. *Belgian Journal of Linguistics*, *25*, 189–206.

Tanenhaus, M. K., Caroll, J. M., & Bever, T. G. (1976). Sentence–picture verification models as theories of sentence comprehension: A critique of Carpenter and Just. *Psychological Review*, *83*, 310–317.

Troiani, V., Peelle, J., Vesely, L., Clark, R., & Grossman, M. (2008). Selective number-related comprehension deficits in corticobasal degeneration. *Neurology*, *70*, A182.

Tsotsos, J. (1990). Analyzing vision at the complexity level. *Behavioral and Brain Sciences*, *13*, 423–469.

Turing, A. (1936). On computable numbers, with an application to the Entscheidungs problem. *Proceedings of the London Mathematical Society*, *42*, 230–265.

Van Benthem, J. (1986). *Essays in logical semantics.* Dordrecht: Reidel.

Van Rooij, I. (2008). The tractable cognition thesis. *Cognitive Science*, *32*, 939–984.

Zajenkowski, M. (2013). Energetic arousal and language: Predictions from the computational theory of quantifiers processing. *Human Factors* (in press).

Zajenkowski, M., Styła, R., & Szymanik, J. (2011). A computational approach to quantifiers as an explanation for some language impairments in schizophrenia. *Journal of Communication Disorders*, *44*, 595–600.

Zajenkowski, M., Szymanik, J., & Garraffa, M. (under review). *Working memory mechanism in proportional quantifiers verification.* (under review).