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Academic achievement in college: the predictive value of subjective evaluations of intelligence and academic self-concept[1]

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Abstract

The study examined the relationship between self-, peer- and test-estimated intelligence, academic self-concept and academic achievement. Subjective evaluations of intelligence and academic self-concept had incremental predictive value over conventional intelligence when predicting achievement accounting for more than 40% of its variance. The obtained pattern of results is presented via SEM-model which accounts for 75% variance in the latent factor of academic achievement. Author suggests the importance of further studying complex sets of achievement predictors from ability, personality and mediating domains.

Keywords: subjective evaluations, intelligence, self-estimated intelligence, academic self-concept, academic achievement

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Introduction

It is not surprising that IQ measures predict educational achievement as they have had a long history of validation specifically against achievement criteria (Deary, Smith, Strand, & Fernandes, 2007; Mackintosh, 2006; Sternberg, 2003). Psychology systematically studied predictive value of intelligence measures in the educational domain and there is little doubt that this value is significant: Correlations between psychometric intelligence and educational achievement are usually moderate to strong (e.g., Deary, Smith, Strand, and Fernandes, 2007; McGrew and Knopik, 1993). However, conventional IQ measures typically explain only about 25% of variance in learning outcomes and their predictive power seems to lower when studied on higher levels of education or in selective samples (MacKinnon, 1962; Grigorenko and Kornilov, 2007; Sternberg, Grigorenko, and Bundy, 2001).

One of the possible ways of increasing the predictive value of intelligence measures is by broadening the concept of intelligence itself. For example, Sternberg's (1999, 2003) triarchic theory of intelligence suggests that relatively independent analytical, practical and creative abilities each make a unique contribution to achievement. This approach addresses previously unexamined types of abilities that play a role in adaptation and achievement; cultural differences in beliefs about abilities that are considered valuable; and students' individual profiles of weaknesses and strengths as well.

Another approach is to study the incremental explanatory power of intelligence measures obtained through self- and other- reports. This approach is of special interest to us because a self-estimated intelligence construct is by definition closely related to a self-concept. Self-estimated (or self-assessed) intelligence represents"individual differences in people's level of awareness of their capacity to perform on intellectually demanding tasks" (Chamorro-Premuzic and Furnham, 2006a, p. 257) and is usually measured with direct self-estimates, Likert scales, percentile ranks, and visual analog scales (see Holling and Preckel, 2005).

It is obvious that if self-estimated intelligence as a measure of one's insight into level of his abilities correlates with actual ability measures, part of its predictive power may come from this correlation. An increasing number of studies showed that these self-evaluations significantly and positively ($r = .14$ to $r = .37$) correlated with conventional IQ measures (Borkenhau and Liebler, 1993; Mabe and West, 1982; Paulus, Lysy and Yik 1998; Rammstedt and Rammsayer, 2002). This means that if self-estimates of intelligence are specific and relatively accurate estimates of abilities, they can be used to predict achievement just as intelligence measures are. Indeed, Chamorro-Premuzic and Furnham (2006b) argue that, unlike other self-evaluation constructs, self-estimated intelligence is an intelligence measure, but a subjective one. However, a view of self-estimated intelligence as a proxy for psychometric measures in studying cognitive predictors of academic achievement is still doubtful (Paulus, Lysy and Yik 1998; but also see Holling and Preckel, 2005) since previous research showed that personality measures explain about 8% in self-estimated intelligence (Furnham and Dissou, 2007); the scores are systematically biased in subsamples and moderated by social comparisons, gender, experience with the tasks applied to assess the ability, and feedback (see Holling and Preckel, 2005, for an overview). Also, just as for academic self-concept, there is also evidence for self-estimated intelligence having motivational effects (e.g., Chamorro-Premuzic and Furnham, 2006a, 2006b).

The facts that discussions on whether self-estimated intelligence is related to intelligence or personality (or both) domains are far from being over, that the actual incremental predictive power of a self-estimated intelligence over conventional intelligence measures has rarely been studied, and that most studies focus on the relationship between self-estimated intelligence and personality traits but not other self-concept components, directed us towards simultaneous investigation of the relatioship between self-estimated intelligence, conventional intelligence measures, self-concept components and achievement and the incremental predictive power of self-estimated intelligence over conventional IQ measure.

Studies of predictive value of self-evaluative components should include not only self-estimated intelligence but also a component of self-esteem in learning (that is also known as academic self-concept in Western psychological literature). Conceptual definitions of academic self-concept include both cognitive (i.e., awareness and understanding of the self and its attributes, Bong and Clark, 1999) and affective components (i.e., feelings of self-worth, Covington, 1984) formed through the normative evaluation of perceived competence. Recent research on interrelations between academic self concept and academic achievement concludes that the relations are reciprocal and mutually reinforcing rather than one-way causal (see Marsh, 1990a, 1990b, Marsh, Trautwein, Lüdtke, Köller, and Baumert, 2005, for an overview): Evidence exists for a significant positive relationship between academic self-concept and achievement (Skaalvik and Hagtvet, 1990; Shavelson and Bolus, 1982; see also Hansford and Hattie's (1982) meta-analysis) with both top-down and bottom-up effects present.

It is also clear that people have perceptions not only of their own abilities, but of others' abilities as well. Kornilova, Smirnov, Chumakova, Kornilov, and Novototskaya-Vlasova (2008) have designed a procedure that provides peer- and self-estimated intelligence scores for a group of students in a single short procedure. This procedure is based on ranking a student's classmates by intelligence based on a list of the class. The specificity of this procedure is that no clear definition of intelligence neither actual information about the distribution of intelligence scores in the population is given. The procedure, called Group Estimation of Intelligence (GEI), is built around: 1) an implicit theories of intelligence[2] construct as a core concept in an individual's evaluation of his and others' abilities; 2) a social comparisons method, which does not require a participant to provide a numerical estimate of his intelligence, but rather compare it with the intelligence of reference group members, namely classmates.

[2] Anoter meaning of this concept is possible and suggests that implicit theories represent beliefs about the content, structure and role of abilities in different life settings (Sternberg, 1995, 2000; see also Furnham, 1988).

These peer ratings may potentially be accurate due to four main reasons. First, students observe their classmates in a variety of intellectually demanding achievement situations. These peer-estimates, just as self-estimates, may act as ability estimates and represent beliefs about someone's abilities. When many experts are involved, their combined scores may be even more precise than self-estimates – such use of multiple informants and the improved accuracy and predictive validity of the scores that come from such multiple feedback, for example, underlie 360-degree assessment technique (e.g., Craig and Hannum, 2006, but also see van Hooft, van der Flier, and Minne, 2006). Second, implicit theories of intelligence themselves represent beliefs about the types of valued behavior that are considered intelligent and leading to success (Sternberg, 2000). Third, since no operational definition of intelligence is given, these estimates possibly reflect beliefs about a broader range of abilities than encompassed by conventional notions of intelligence. Thus, these peer-estimates may reflect not only analytical, but other forms of intelligences as well (e.g, social, practical or emotional), thus tapping variance from multiple sources. Fourth, there is some evidence for motivational and self-fulfilling effects of other-estimates of abilities (see Furnham, 2001, for an overview): These self-fulfilling effects are often discussed in their relation to widely known Pygmalion effect.

Although there have been studies of subjective evaluations of intelligence focusing on self- and relatives-estimates of abilities, peer-estimates were somewhat excluded from this list (except for studies of relatively young children's perception of other children's abilities, e.g., Hughes and Zhang, 2007; Simpson and Rosenholtz, 1986; Stipek and Tannatt, 1984). The present study examines 1) the incremental predictive validity of peer-estimated intelligence scores generated by multiple students over conventional intelligence and 2) its relationship with actual and self-estimates of ability which the author consider to be precise and predictive due to the reasons mentioned above. The study also aims at 3) fitting the SEM-model that includes subjective evaluations of intelligence and academic self-concept predicting academic achievement in students.

Although this study explicitly aims at revealing the predictive value of academic self-concept and self-estimated intelligence, it is important to note that within the cultural-historical and activity frameworks these components are viewed as functioning in the learning activity withing dynamic regulative systems in which they are connected with other components of a self-concept and motivation.

L. Vygotsky's (1962) idea that thought is born, not from another thought, but from the motivating sphere of consciousness became a leading principle in understanding sense regulation of thinking (Tikhomirov, 1977, 1984) with another level of regulation being related to the self-consciousness: both self-evaluation and sense direct thinking in learning. In Russian psychology, this is reflected in the idea that the self-consciousness is a top level in the system of personality regulation of activity (Leontiev, 1978; Stolin, 1983).

The learning activity in a university/college suggests multiple intellectual decisions. Not only intelligence contributes to the achievement of learning goals, but beliefs about which goals are reachable. These beliefs are, in turn, influenced by motivation and values, resulting in emotional evaluation of specific goals that, along with beliefs about one's intellectual potential, includes in the developing self-concept. Thus, not only abilities regulate learning activity, but so-called dynamic regulative systems in which different psychological attributes form an integrated whole, rather than being relatively independent and separate factors (Kornilova, 2008; Kornilova and Smirnov, 2002).

The present paper examines the impact of these DRSs as self-regulation units on learning outcomes in a real-life university setting. In this case, implicit components of a self-concept may be related to sense formations which are only partially conscious. We argue that dynamic regulative systems include both conscious and unconscious levels of psychological components, which are integrated by components of integral self-regulation, and that both levels include self-evaluation components.

The following hypotheses will be tested in this study:

H1. Components of a self-concept and subjective evaluations of intelligence will have incremental predictive power over a conventional intelligence measure in predicting learning outcomes.

H2. Measured and peer-estimated intelligence and the academic self-concept and self-estimated intelligence will form two distinct latent factors, respectively, and these correlated factors, as functioning within a dynamic regulative system, will predict achievement.

Method

Participants

Three hundred undergraduate students (73.7% female, the mean age was 19.48, SD = 1.98) from two departments at MSU (Moscow State University) participated in this study in return for course credit. The first group were 224 psychology majors (83.5% female, Mean age = 19.62, SD = 2.29) taking an experimental psychology course and the second group were the 76 biocomputer science and engineering majors (44.7% female, Mean age = 19.10, SD = .61) taking an introductory psychology course.

Procedure

First, we administered the Implicit Theories Inventory to the students. The next week participants went through the GEI procedure. A week later, the participants completed the IST-70 test. At the end of the semester, academic achievement records were obtained. Students did not receive any feedback until the study was over. All missing data in the sample were managed using the pairwise maximum likelihood (pairwise ML) method as implemented in EQS 6.1 (Bentler, 1995) software. The pairwise ML method (Savalei and Bentler, 2005) provides computed statistics for correlations based on all available cases that have scores on pairs of variables. Thus, it is possible to avoid case elimination and score imputation. Computed ML estimators are then corrected for non-normality as in the Satorra-Bentler approach. This method is known to provide accurate parameter estimates, but somewhat inflated test statistics.

Measures

Academic achievement. We collected students' *GPA* for the three semesters through official transcripts as a baseline measure of academic achievement prior to testing. For 44 students there were no records at the time this study was conducted. Preliminary analysis of the distribution of GPA scores ($M = 4.48$, $SD = .41$ on a 1 to 5 scale) has shown that it significantly differs from a normal distribution (Kolmogorov-Smirnov $Z = 1.661$, $p < 0.01$; skewness = - .671; kurtosis = -.26).

175 psychology majors also received a grade in an experimental psychology course *(EXP*; $M = 3.75$, $SD = 1.30$) and 70 biocomputer science majors received a grade in a biochemistry course *(BIO*; $M = 4.11$, $SD = 1.06$). We used these measures as complementary to GPA for two reasons: 1) students rated these courses as the most difficult in the psychology and biocomputer science programs, respectively (data on students' ratings were obtained through the Educational Boards of the departments); 2) recent studies have shown that students at MSU (and in most cases – other universities as well) typically have a relatively high GPA ($M = 4.53$, $SD = .45$ as reported by Grigorenko and Kornilov, 2007) and the variance in GPA is quite limited; 3) these measures were collected at the end of the semester and, therefore, assume a significant time lag between going through the assessments used in this study and receiving a grade. Compared to GPA, the complementary measures as presented in a grade received for a difficult exam addressed more variance in academic achievement. Exam scores were also standardized within the two groups of students.

Implicit Theories Inventory. Academic self-concept was measured using the Russian version of the *academic self-concept* scale (ASC). This measure represents a student's beliefs about the overall effectiveness of their learning activity and subjective value of efforts put into the learning activity, and whether a student tends to think that he or she is among successful students. For example, a student is asked to agree or disagree with the following statement: "You put forth maximum efforts to master knowledge and skills and that's why you're sure you'll become a high-level professional." The inventory was first published in Russian by Kornilova, Smirnov, Chumakova, Kornilov, and Notovotskaya-Vlasova (2008). They have reported moderate reliability score of .73 for the newly developed ASC scale. The study also showed the moderate ($r = .60$) predictive validity of the ASC scale in academic achievement.

Self and peer-estimated intelligence. Unlike traditional direct self-estimates of intelligence obtained through giving a numerical estimate of intelligence with reference to the normal distribution (Bennett, 1996; Furnham and Rawles, 1999) or a Likert-scales based one (Fingermann and Perlmutter, 1994; Paulus, Lysy, and Yik, 1998), the Group Estimation of Intelligence (GEI) procedure facilitates social comparisons within a specific reference group. We have asked students to range themselves and their classmates by perceived "intelligence" based on the list of their class, preliminarily having written which qualities a person whom they consider to be clever should possess. A weighted mean rank of a student in a group - a variable *of a peer-estimated intelligence (PEI)* - is computed. A weighted rank that a student assigned to himself is used as a measure of his *self-estimated intelligence (SEI)*. Students have gone through the GEI procedure prior to intelligence testing so they could not base their estimations on feedback received from their classmates after the completion of the IQ test.

Cognitive ability. Intelligence was assessed with the IST-70 (Amthauer, 1973) test, which contains the following sub-scales: sentence completion, verbal classification, verbal analogies, and verbal concept formation (% of correct responses in these subtests is a *Verbal IQ* score); numerical tasks, and number series (*Mathematical IQ*); figure matching, and spatial orientation (*Spatial IQ*) and memory.The Russian version of the IST-70 intelligence test (Gurevich, Akimova, Kozlova, and Loginova, 1993) was administered in groups of ~20 students (total $n = 238$). The test contains abstract figural reasoning tasks as markers of fluid intelligence, and knowledge items as markers of crystallized intelligence, which form the three subscales mentioned above and the *General IQ* scale as well. Due to time limitations, we could not include the last subtest, memory, in our study. The test scores were normally distributed.

Results

Internal-consistency reliability (α coefficient) for the ASC scale was .76 which is satisfactory and generally replicates the one reported by Kornilova, Smirnov, Chumakova, Kornilov and Novototskaya-Vlasova (2008). For the IST-70 test, reliabilities were .67 for the total General IQ score (.46 for Verbal IQ, .87 for Mathematic IQ, and .70 for Spatial IQ). The verbal intelligence subtests from the Russian version of the IST-70 have not been revised for a long time and we expected their internal consistency to be lower.

Table 1
Intercorrelations[a]

Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) ASC	1	209	209	209	209	186	211	213	208
(2) General IQ	.08	1	238	238	238	184	203	204	193
(3) Verbal IQ	.06	.82**	1	238	238	184	203	204	193
(4) Math IQ	.08	.84**	.52**	1	238	184	203	204	193
(5) Spatial IQ	.04	.67**	.31**	.43**	1	184	203	204	193
(6) SEI	-.33**	-.23**	-.32**	-.14	-.02	1	207	175	167
(7) PEI	-.40**	-.37**	-.30**	-.34**	-.22**	.27**	1	215	209
(8) GPA	.60**	.27**	.24**	.24**	.11	-.27**	-.66**	1	229
(9) Exam in a field of major	.47**	.15*	.14	.14*	.04	-.18*	-.49**	.60**	1

[a]Below the diagonal are the correlations for the combined sample; the n's are presented above the diagonal.
*P < .05
**P < .01

Self- and peer-estimated intelligence correlated positively at .27 (p < .01, n=207). Both self-estimated and peer-estimated intelligence were positively related to General, and Verbal IQ (-.23, p < .01, n=184, -.32, p < .01, n=184, respectively, for SEI, and -.37, p <.01, n= 203, -.30, p < .01, n=203, respectively, for PEI), but correlations with Math IQ and Spatial IQ were established only for peer-estimated intelligence (-.34, p < .01, n=203 and -.22, p <.01, n=203, respectively. These results suggest that peer-estimated intelligence scores, probably due to their composition of a numerous assessments of students' abilities by most of their classmates, encompass a wider range of abilities than self-estimated intelligence, and, according to stronger correlations, do so more accurately. Another reason for this pattern of results may be that peer- and self-estimates rely on distinct bases of evaluations.

General IQ, Verbal IQ, Math IQ positively correlated with students' GPA (.27, .24, .24, $p < .01$, $n=204$, respectively). However, only General and Verbal IQ (.15, .14, $p < .01$, $n=193$, respectively) appeared to be related to exam results. This may have happened due to non-significant correlations between IQ measures and exam results for the biocomputer science majors.

The correlations between self-estimated intelligence and achievement in the total sample were - .27 ($p <.01$, $n = 175$) for GPA and -.18 ($p < .05$, $n=167$) for exam results, but were non-significant for biocomputer science majors. Partial correlations were $r = -.23$ ($p < .01$) and $r = -.11$ ($p < .05$). Peer-estimated intelligence correlated with GPA at $r = -.65$ ($p < .01$, $n=215$) and exam results at $r = -.43$ ($p < .01$, $n=209$) with partial correlations of -.62 and .42, respectively.

Academic self-concept scale positively and significantly correlated with GPA (.60, $p < .01$, $n=213$) and exam results (.47, $p <.01$, $n=208$). When age, sex, intelligence and field of study were controlled, the partial correlations remained significant and lowered a little (.59 and .43 for GPA and exam, respectively).

Hierarchical linear regressions were performed to investigate the incremental predictive validity of self-, peer-estimated intelligence and academic self-concept over the conventional IQ measures. The results are summarized in Table 2. Sex and age were entered in the first step and predicted about 1% of the variance of GPA. Test-estimated IQ variables, entered in the second step, added 7% more to the explanatory power of the model. Self-estimated intelligence had incremental predictive power of about 3%. Neither implicit theories nor goal orientations had significant predictive power. The most dramatic increase in predictive power was when peer-estimated intelligence scores and academic self-concept were entered into the model (23% and 14% of unique variance explained, respectively). Thus, as predicted, academic self-concept as a self-concept component in the learning domain revealed a significant predictive power over other measures in this study.

Table 2
Hierarchical regressions: test-, self-, peer-estimated intelligence and academic self-concept predict GPA

	β	t	Model summary
Model 1			Adj. R^2 = .01
Sex	-.12	-1.58	F(2,172) = 1.94
Age	-.07	-.93	MS = 1.91, .99
Model 2			Adj. R^2 = .08
Sex	-.19*	-2.44	F(5,169) = 4.08**
Age	-.00	-.01	MS = 3.73, .91
Verbal IQ	.14	1.59	R^2 change for IQ scales
Mathematical IQ	.21*	2.24	Δ R^2 = .09
Spatial IQ	.01	.06	
Model 3			Adj. R^2 = .11
Sex	-.20*	-2.62	F(6,168) = 4.65**
Age	-.01	-.18	MS = 4.12, .89
Verbal IQ	.08	.93	R^2 change for SEI
Mathematical IQ	.21*	2.31	Δ R^2 = .04
Spatial IQ	.01	.06	
SEI	-.19*	-2.61	
Model 4			Adj. R^2 = .35
Sex	-.16*	-2.49	F(7,167) = 14.37**
Age	.10	1.51	MS = 9.31, .65
Verbal IQ	.08	1.06	R^2 change for PEI
Mathematical IQ	.12	1.53	Δ R^2 = .23
Spatial IQ	-.04	-.53	
SEI	-.03	-.40	
PEI	-.54**	-7.90	
Model 5			Adj. R^2 = .49
Sex	-.02	-.34	F(8,166) = 22.32**
Age	.03	.47	MS = 11.23, .50
Verbal IQ	.12	1.80	R^2 change for ASC
Mathematical IQ	.07	1.03	Δ R^2 = .14
Spatial IQ	-.04	-.62	
SEI	.07	1.10	
PEI	-.39**	-6.02	
ASC	.45**	7.00	

*P < .05
**P < .01

To integrate the patterns of relationships between independent and dependent variables discussed in the above sections, we have fitted a number of structural equation models, we also defined a model, initially proposed by Kornilova (2008) in terms of the variables in our study. In this model, four latent factors are introduced. The achievement factor is that of the previous model; the intelligence factor is comprised of test-derived scores (a latent factor as in previous model) and peer-evaluations of intelligence; the last factor, of self-concept, is defined by self-estimated intelligence and academic self-concept. The two main factors, of self-concept and of intelligence, are correlated and predict achievement.

The fitted model is shown in Figure 1. The model provided satisfactory fit: $\chi^2(16) = 24.28$, $p > .08$, RMSEA = .042, CFI = .98. In general, the model suggests that the relationship between self-estimated and psychometric intelligence scores is also mediated by a correlation between higher-order factors of intelligence and self-concept. Together, intelligence and self-concept factors had the predictive validity of 75% of the variance in GPA.

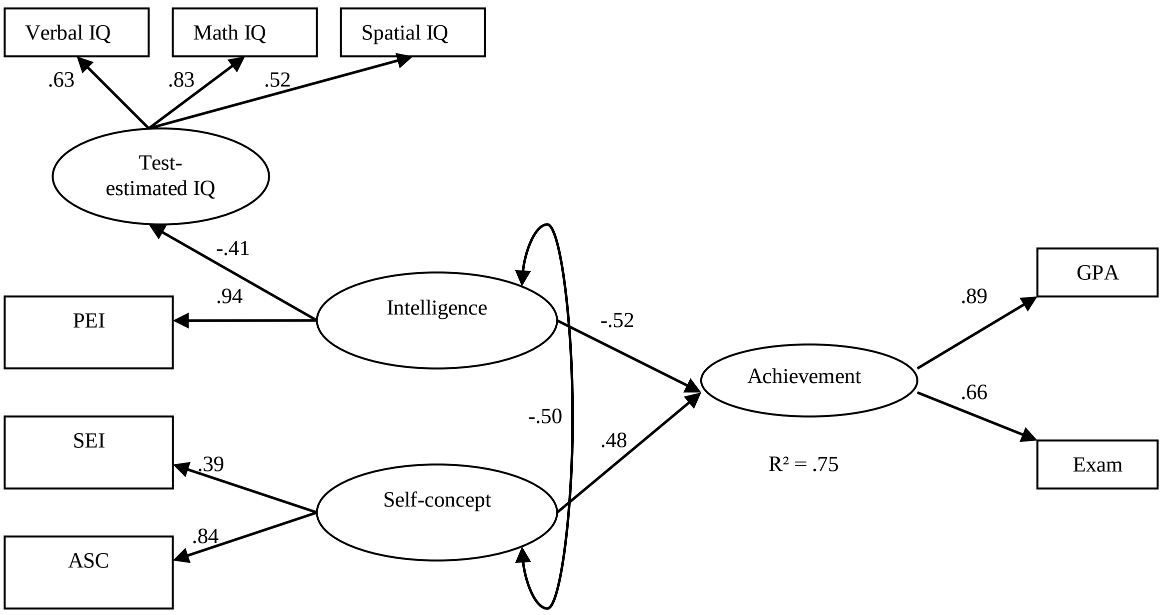

Figure 1. A diagram for the fitted SEM-model.
SEI – Self-estimated intelligence; PEI – Peer-estimated intelligence; ASC – Academic self-concept. Only significant coefficients are shown.
Note: negative signs for Intelligence factor actually represent positive relationship since this variable was defined through PEI indicator variable (higher values mean lower estimates): i.e, Intelligence latent factor is positively related to Test-estimated IQ, PEI, Self-concept and Achievement factors.

Discussion

In general, the results of the study are in line with the findings suggesting that both g and verbal ability are highly predictive of a variety of important outcomes, including educational attainment, academic achievement and job performance (e.g., Gottfredson, 1997; Kuncel, Hezlett, and Ones, 2004; Mackintosh, 2006). The results obtained in this study also expand the notion of self-estimated intelligence: Although others suggest that self-estimated intelligence may be viewed as a subjective IQ measure and validated against academic performance (Chamorro-Premuzic and Furnham, 2006a, 2006b), in our study self-estimated intelligence positively correlated not only with the psychometric intelligence, but with academic self-concept as well. Moreover, the model proposed in this study provided evidence for viewing self-estimated intelligence as being a component of a self-concept along with the academic self-concept, confirming that self-estimated intelligence is related to personality measures (Chamorro-Premuzic, Furnham, and Moutafi, 2004; Chamorro-Premuzic, Moutafi, and Furnham, 2005) and contributes to a higher-order factor of a general academic self-concept, although in other study this overlap is somewhat smaller (e.g., Peterson and Whiteman, 2007).

As mentioned above, the study examined the relationship between psychometric intelligence, subjective evaluations of intelligence and achievement and found that both psychometric intelligence and its subjective estimates were related to achievement. The coefficients were comparable for self-estimated and psychometric intelligence and were dramatically higher for peer-estimated intelligence. Students have insight into the level not only of their own, but of others' abilities as well and evaluations based on this accurate insight are highly predictive of academic achievement even when controlled for conventional measures of IQ. The fact that peer-estimates proved to be more predictive than self-estimates, were more accurate and tapped a wider range of abilities (i.e., including also numerical and spatial intelligence versus general/verbal scores for self-estimates) can be interpreted in a few ways. We think that although obtained through the single procedure, peer- and self-estimates of intelligence are based on different criteria. Both peer- and self-estimates inevitably rely on lay conceptions of abilities but peer-estimates seem to incorporate a wider range of ability-related criteria (i.e., including non-academic forms of intelligence, see Sternberg, 1985, 2006; Gardner, 1983, 1999, for an overview) and overall evaluation of activities and achievements seen as crucial for academic success (i.e., overall goal achievement, various educational outcomes, participation in extracurricular activities).

Our study also revealed the incremental predictive value of subjective evaluations of intelligence and academic self-concept over conventional intelligence in predicting achievement. In this study, peer-estimated intelligence and academic self-concept had the largest contribution to achievement. When sex, age, field of study and intelligence were taken into account, subjective evaluations of intelligence and academic self-concept accounted for an additional 41% of the variance in GPA. Note that when peer-estimated intelligence was entered into the model, General IQ and self-estimated intelligence lost their predictive power which speaks in favor of assuming that peer-estimated intelligence measure encompassess a wider range of ability and non-ability criteria than conventional and even self-estimated intelligence, as mentioned above.

The significant positive relationship between academic self-concept and achievement obtained in this study is consistent with a growing body of research documenting positive correlations between academic self-concept and achievement (Hansford and Hattie, 1982; Marsh, 1987, 1993; Marsh, Trautwein, Ludtke, Shavelson and Bolus, 1982; Skaalvik and Hagtvet, 1990), although in this study the relationship is notably stronger ($r = .60$). The recently developed reciprocal effects model states that prior achievement affects subsequent academic self-concept and vice versa and strong support has been found for this model (e.g., Marsh, 1990b; Marsh and O'Mara, 2008; Marsh, Trautwein, Lüdtke, Köller, and Baumert, 2005). As predicted (e.g., Marsh and Yeung, 1997, 1998) the present study also shows that the relationship between academic self-concept and achievement and the predictive value of self-concept components is especially strong when achievement is based on high-stakes grades in a highly selective population of university students.

A more general interpretation of the results obtained in this study is possible within the dynamic regulative systems framework (Kornilova, 2008; Kornilova and Smirnov, 2002). When examining these systems, a researcher may include different processes and a different number of processes in a model of a regulation of the learning activity. For example, structural equation model fitted in this study showed that latent factors of intelligence and self-concept are significantly and positively related and together explain about 75% of the variance in the latent achievement factor, suggesting that self-estimated intelligence should be viewed as a personality rather than ability measure; that self- and peer-estimates of intelligence are based on different evaluation criteria; that subjective evaluations of intelligence and academic self-concept have significant incremental predictive power over conventional measures of intelligence when predicting academic achievement in college/university students.

Conclusion

Our results are largely consistent with the recent research suggesting the significant predictive value of self-concept components when predicting achievement in university students documenting the incremental predictive value of academic self-concept and subjective evaluations of abilities, that may and do tap a wider range of abilities (and achievement criteria) than conventional intelligence measures.

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