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Program-specific prediction of academic achievement on the basis of cognitive and non-cognitive factors

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A B S T R A C T

Choosing a suitable study program is one of the factors that facilitates academic achievement and thus prevents drop-out in the first year of tertiary education. This requires adequate information on both the individual abilities and the environment during the study choice process. The SIMON (Study Skills and Interest MONitor) project of Ghent University, Belgium, provides this information to prospective students through an online tool that informs them a) on the match between their interests and study programs and b) about their personal chances of success in specific study programs. The current study intends to validate the prediction of program-specific chances of success by examining a) the (incremental) predictive validity of cognitive and non-cognitive variables of conscientiousness, motivation, self-efficacy, metacognition and test anxiety and b) the differential predictive power of variables within and across study programs. In addition, a path model with structural relations between variables was tested. The sample consisted of 2391 new incoming students.

Results supported the incremental validity of non-cognitive factors. Achievement could be predicted by cognitive and background factors and by conscientiousness, self-efficacy and test anxiety. Moreover, the predictive power of variables varied across study programs, which suggests that research findings about the prediction of academic achievement might benefit from taking into account the specific program context.

Practical implications for research and (educational program choice) counselling of students are discussed.

1. Introduction

1.1. Study context: flanders and the SIMON project

Drop-out rates in higher education are high. The Organization for Economic Co-operation and Development reported that 32% of incoming tertiary students do not graduate from a program at this level (OECD, 2008). Vocational choice, and more specifically choice of program of study or major, is certainly an important topic in this matter. According to person-environment fit theories, choosing an educational program that fits the individual is one of the factors that facilitates academic success and can thus prevent drop-out in the first year of tertiary education. For example, the Minnesota Theory of Work Adjustment posits that a person's achievement and satisfaction is predicted from the correspondence between the abilities of the person and the ability requirements of the environment (Dawis, 2005). In order to make an optimal study choice, adolescents should identify their values and abilities, as well as the educational possibilities that correspond with these values and abilities (Swanson & Schneider, 2013). This requires adequate information on both the individual and the environment during the study choice process. When potential students are able to assess their personal abilities and their fit with educational programs, this may increase student retention (McGrath et al., 2014). Moreover, providing an instrument that assesses these factors may increase social equality in higher education as it are often socially vulnerable groups that lack the information to make a realistic educational program choice or to enroll in tertiary education (Müller, 2014; OECD, 2003).

Although universally relevant, such an assessment tool is especially valuable in the current study context, Flanders, which is the northern region of Belgium. Flanders has a public education system where access to higher education is almost unconstrained. The majority of higher education systems across the world use some form of examination (e.g., the Scholastic Aptitude Test in the US) or rely on a minimal secondary education academic performance in the admission process. In Flanders, however, admission restrictions virtually don't exist. Any student with a secondary education qualification can enter almost any higher education institution and field of study. With the exception of medicine, dentistry and performing arts programs, there are no selection exams, there are no entrance quota and secondary education Grade Point

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Average (GPA) is never considered for admission. On top of that, tuition fees are extremely low (below $1000 per year). This system is assumed to foster social mobility and to improve participation of economically disadvantaged groups in higher education, but the open entrance implies de facto that the first year of university is typically a “selection year”. Less than 40% of university students pass all courses during the first year of studying (even after repeated examination attempts). This is alarming, especially because first year performance is one of the best predictors of academic retention (de Koning, Loyens, Rikers, Smeets, & van der Molen, 2012; Murtaugh, Burns, & Schuster, 1999).

In addition to open access, students must enroll in a specific study program and select a major already at the start of higher education. Therefore, in the current paper the term ‘study program’ refers to both the choice of program of study and of the specific major. Switching programs usually requires students to restart as a freshman. Taken together, the study options are numerous and (financial and motivational) consequences of selecting an inappropriate program are high. This context makes the study orientation process even more important and the provision of adequate information on the match between a prospective student and a specific study program even more crucial.

In response to these challenges, Ghent University started the SIMON-project (Study skills and Interest MONitor), developing a freely available online assessment tool by which students can assess their interests (SIMON-I, Fonteyne, Wille, Duyck, & De Fruyt, 2016) and competencies (SIMON-C). As admission is free by law, SIMON is not an admission tool, but it is designed to provide prospective students (*before* enrollment) with relevant information on the match between their interests/competencies and study programs and on program-specific chances of success in tertiary education. The assumption is that adequate and personalized information will help students to make better higher education study choices. As stated by McGrath et al. (2014), this can be achieved by introducing non-selective entry tests and strengthening pre-university orientation, which is exactly the objective of the SIMON-project.

The focus in the current study is on the evaluation of competencies with regards to specific study programs (SIMON-C). As such, its purpose is to identify whether prospective students have low chances of success in specific study programs, based on historic data of students with comparable abilities. In contrast with high-stake admission tests, SIMON-C's discriminatory power lies at the lower end of the ability range: its aim is to identify a small group of students that has a very low probability of passing. This is also in accordance with the open access policy: only potential students who almost certainly lack the very basic abilities to succeed (should) get a clear warning, yet, students who may be vulnerable but who might still be able to pass get the benefit of doubt and are not be discouraged. In short, SIMON-C targets to predict tertiary academic achievement (and especially failure) relying on the student's skills and abilities. Assessment of skills and abilities in SIMON-C was based on the vast amount of studies pertaining to the prediction of academic success and retention.

1.2. What factors predict academic achievement?

1.2.1. Cognitive factors

The use of cognitive ability to predict academic success has a long standing tradition. In fact, the first broad test of cognitive ability (the Binet-Simon scale in 1905) was specifically designed to predict achievement in an educational context. Since then, cognitive ability, or g (a construct related to fluid intelligence) has been consistently found to predict academic achievement (Ackerman & Heggestad, 1997; Busato, Prins, Elshout, & Hamaker, 2000; Farsides & Woodfield, 2003; Kuncel, Hezlett, & Ones, 2004). As the importance of cognitive ability for academic achievement has been well documented, a detailed overview is beyond the scope of this study. It suffices to say that many authors argue that cognitive ability is (one of) the strongest predictor(s) of academic performance (Kuncel & Hezlett, 2010; Petrides, Chamorro-Premuzic, Frederickson, & Furnham, 2005), with correlations with GPA ranging from 0.30 to 0.70 (Roth et al., 2015). As a result, it is mainly cognitive ability that is tested for admission decisions in countries with restricted access to higher education. Most of these tests assess a combination of verbal and quantitative skills (Sedlacek, 2011).

In many predictive studies of academic achievement, previous academic achievement (often high-school GPA) is also taken into account. However, high-school GPA has the great disadvantage that it is not comparable across high schools (and even teachers). Moreover, studies indicate that grades have become a less useful indicator of student success, mainly because of “grade inflation” (Sedlacek, 2011). Therefore, in the current study we included hours of mathematics instruction in secondary education as a background factor, as previous data and research have shown that this is a relevant predictor in the current study context (Fonteyne et al., 2015). Note that Flanders does not have a common, standardized exam (like the SAT) at the end of secondary education.

1.2.2. Non-cognitive factors

Although cognitive factors are highly relevant in the prediction of academic achievement, correlations between ability measures and academic performance are lower at more advanced levels of education (Boekaerts, 1995), which is generally explained by range restriction effects (e.g., Furnham & Chamorro-Premuzic, 2004; Richardson, Abraham, & Bond, 2012; Sternberg, Grigorenko, & Bundy, 2001). Also, some students fail in spite of high cognitive ability and some students compensate a lack of cognitive or test-taking ability by showing greater motivation or effective study strategies (Komarraju, Ramsey, & Rinella, 2013). Therefore, assessment of other factors is also valuable.

Allen, Robbins, and Sawyer (2009, p.2) define non-cognitive factors as “nontraditional predictors that represent behavioral, attitudinal, and personality constructs, primarily derived from psychological theories”. ‘Non-cognitive’ refers to a variety of constructs. As a result, several classifications have been proposed. De Raad and Schouwenburg (1996) noted that Messick (1979) provided an encompassing list of potential non-cognitive factors, which included background factors, attitudes, interests, temperament, coping strategies, cognitive styles, and values. Lipnevich and Roberts (2012) proposed a taxonomy of four categories: attitudes and beliefs (self-efficacy), social and emotional qualities, learning processes and personality. Sedlacek (2010) mentioned, apart from others, positive self-concept, realistic self-appraisal and also the ability to handle racism. This shows that the classification of these constructs is not straightforward which prompts a selection of relevant predictors depending on the context.

Apart from cognitive factors, personality has been proposed as one of the main determinants of academic achievement arguing that cognitive factors would measure maximal performance (what can the student do?) whereas personality would account for typical performance (what will the student do?) (Chamorro-Premuzic, Furnham, & Ackerman, 2006). Indeed, many studies have shown that (Big Five) personality factors add incremental predictive validity for academic achievement over and above cognitive factors (see e.g., Poropat, 2009). Especially *Conscientiousness* has been raised as an important predictor for academic success (Conard, 2005; Noftle & Robins, 2007; Poropat, 2009; Trapmann, Hell, Hirn, & Schuler, 2007). Therefore, conscientiousness was included in the current study.

As for other non-cognitive constructs, we chose to include only factors for which predictive validity for academic achievement has been demonstrated over and above cognitive factors. This allowed to limit testing time and was in accordance with our aim to advise prospective students based on a scientifically valid tool. We turned to meta-analyses to identify such non-cognitive constructs as these summarize the results of multiple studies and therefore generate more robust estimates of reliable effect sizes. We came across two large meta-analyses that fit our purposes. They are both well cited and examined the effect of non-cognitive constructs over and above cognitive predictors.

A first is a study by Robbins et al. (2004), which included 109 studies. They found that the best non-cognitive predictors of college GPA were academic self-efficacy and academic motivation (ρs 0.50 and 0.30, respectively). Academic self-efficacy was a better predictor than both high school GPA and ACT/SAT scores (ρs 0.45 and 0.39, respectively). A second meta-analysis (by Credé & Kuncel, 2008) examined the incremental validity of study skills, habits and attitudes such as self-regulatory skills and time management. They found that study motivation and study skills exhibit the strongest relationship with GPA (ρs 0.39 and 0.33, respectively). Academic-specific anxiety was an important negative predictor of performance (ρ = − 0.18). Based on these studies, we chose to include these relevant variables in our research.

Robbins et al. (2004) identified academic self-efficacy as an important predictor. Self-efficacy (Bandura, 1997) is described as ‘beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments’. Choi (2005) and Pajares (1996) demonstrated that particularized measures of self-efficacy have better results in the prediction and explanation of related outcomes. As a consequence, academic self-efficacy has been empirically related to academic achievement (Bong, 2001; Chemers, Hu, & Garcia, 2001; Choi, 2005; Elias & Loomis, 2002; Galyon, Blondin, Yaw, Nalls, & Williams, 2012; Lent, Brown, & Larkin, 1986; Multon, Brown, & Lent, 1991; Owen & Froman, 1988; Vuong, Brown-Welty, & Tracz, 2010; Zajacova, Lynch, & Espenshade, 2005). Ferla (2008) found that academic self-efficacy explained 7.4% of the variance in Psychology and Educational Sciences students' academic performance. Therefore, academic self-efficacy could not be lacking in the current study. Still, some have argued that high self-efficacy has detrimental effects. For example, Vancouver, Thompson, Tischner, and Putka (2002) have found a negative relationship between self-efficacy and performance. This might be a result of high self-efficacy leading to diminished effort which in turn affects performance negatively (Vancouver & Kendall, 2006). As a result, it may be reasonable to distinguish several dimensions of self-efficacy, which we took up in the current study. We examine two dimensions of self-efficacy: one called ‘effort’ (the confidence one has that one will put in the effort to succeed) and ‘comprehension’ (the confidence one has that one will understand the contents of the courses). While the first is expected to have a positive relation with academic achievement, the latter may indicate an overestimation of one's abilities which leads to a decrease in effort and results in lower performance.

Study motivation predicted academic achievement in both meta-analyses. We used motivation from a self-determination perspective (SDT). In SDT, motivation is multidimensional in that it distinguishes two qualities of motivation (Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009): autonomous and controlled. Autonomous motivation involves engaging in an activity out of personal interest or relevance. In contrast, controlled motivation involves doing a task with a sense of pressure or guilt. Deci and Ryan (2000) noted a convergence between SDT and Achievement Goal Theories (e.g., Dweck, 1986). According to these authors, autonomous motivation is practically equivalent to learning goals. Yet, they also state that performance goals do not align well with the construct of controlled motivation because performance goals can also be pursued for autonomous reasons. We follow their argumentation that it is necessary to not only consider *what* goals people chase (e.g., performance goals), but also *why* they pursue them (for autonomous or controlled reasons). Therefore, we included motivation from an SDT perspective. Motivation has been shown to impact academic performance, with positive effects for especially autonomous motivation (Bailey & Phillips, 2015; Kusurkar, Ten Cate, Vos, Westers, & Croiset, 2013; Taylor et al., 2014). For example, Vansteenkiste, Zhou, Lens, and Soenens (2005) found that autonomous motivation accounted for 6% of the variance in exam performance of Chinese students.

Credé and Kuncel (2008) emphasized self-regulatory skills as important factors, which refer to the processes which maintain the cognition, affect, and behavior necessary to achieve intended goals (Schunk & Zimmerman, 1997). Cognitive components of self-regulation such as metacognition have been studied. Spada and Moneta (2014) showed that maladaptive metacognition promotes a surface approach to learning (r = 0.42) which in turn leads to poor academic performance (r = − 0.33). González and Paoloni (2015) found that autonomy support, motivation and the metacognitive strategies of planning, monitoring and evaluation explained 57% of the variance of the grade in a chemistry course.

Effects of test anxiety, which was also identified in the meta-analysis of Credé and Kuncel (2008), on performance have been somewhat mixed. De Raad and Schouwenburg (1996) stated that correlations between test anxiety and academic performance are generally low, with typical values between 0.10 and 0.20. On the other hand, numerous studies have supported that test anxiety does have a detrimental effect on performance (see for example Byron & Khazanchi, 2011; Eysenck, Derakshan, Santos, & Calvo, 2007; Hembree, 1988; Hill & Wigfield, 1984). A possible explanation for these opposing findings is that studies measure different aspects of test anxiety. Liebert and Morris (1967) introduced the idea that test anxiety consists of two components: worry and emotionality. Worry refers to the cognitive concern about test taking and performance, such as negative expectations, preoccupation with performance, and potential consequences. Emotionality refers to perceived physiological reactions, that is, autonomic arousal and somatic reactions to testing situations such as nervousness and tension (Hong & Karstensson, 2002). Since then, this bi-dimensionality has been widely accepted (Cassady & Johnson, 2002) and research has indicated that it is especially the cognitive – or worry – component that (negatively) influences achievement (Kitsantas, Winsler, & Huie, 2008; Morris, Davis, & Hutchings, 1981; Seipp, 1991), which is thus included in the current study.

1.2.3. An integrative model

The structural relationship between most of these variables has previously been addressed in the control-value theory of achievement emotions (Pekrun, 2006). Of the variables included in the present study, he proposed that achievement emotion (test anxiety) is influenced by motivation and self-efficacy and that all of these, combined with cognitive and metacognitive factors, affect performance. The current study allows us to test this model and to extend it by adding conscientiousness since personality was not included in his control-value theory of achievement emotions.

1.2.4. Combination of predictive factors

Research has shown that cognitive factors as well as non-cognitive skills predict tertiary academic achievement, yet simultaneous investigations of these conceptually very different factors are scarce, and most studies focus on a specific antecedent of academic success. Also, some studies include variables that are not measurable before, or at the start of tertiary education and therefore did not allow prediction of academic performance *before* enrollment, as is our goal. Exemplary is a Dutch study by de Koning et al. (2012), in a sample of 1753 students, which was nevertheless restricted to a Psychology program. They showed the relative contribution of observed learning activities, first- and second-year performance, high school grades, conscientiousness, and verbal ability towards academic achievement in the bachelor program (R^2 = 0.30). Likewise, Dollinger, Matyja, and Huber (2008, US, N = 338), examined verbal ability, the five-factor model, GPA, academic goals, attendance and study behavior to predict academic achievement in a Psychology course (R^2 = 0.46).

Other studies are more in line with our objective to make predictions based on start-of-the-year competencies, yet they do not include all of the variables that are currently under scrutiny. For example, personality factors were not included in a study by Kitsantas et al.

(2008). They did however find that 47% of the variance in students' academic achievement was accounted for by the combination of prior ability levels (cumulative high school GPA and verbal and math SAT scores), self-regulatory processes, and motivational beliefs (US sample, $N = 243$). Personality variables were also missing in a study by Olani (2009), as were metacognitive skills and test anxiety. With regards to other variables, they found that the combination of prior academic achievement (preparatory school GPA, aptitude test scores, and university entrance exam scores) and psychological variables (achievement motivation and academic self-efficacy) accounted for 17% of the variance in students' university GPA scores. The sole contribution of psychological variables was 4% (Ethiopia; $N = 214$, from departments of Electrical Engineering, International Trade and Investment Management, Information System Management, Mathematics and Psychology).

The Ridgell and Lounsbury (2004) study (US, $N = 140$) did include personality, but left out metacognitive skills, test anxiety and motivational factors. General intelligence, (big five) personality traits and work drive explained 24% of the variance of course grade in introductory psychology and of self-reported GPA.

Thus, none of these studies combined cognitive ability measures with personality, motivation, self-efficacy, metacognition and test anxiety in the prediction of academic success. To our knowledge; only one study did include all factors currently under scrutiny. Richardson et al. (2012) conducted a meta-analysis of 55 European and 186 Northern American data sets that included demographic factors, measures of cognitive capacity or prior academic performance and 42 non-cognitive constructs from 5 research domains: (a) personality traits, (b) motivational factors, (c) self-regulatory learning strategies, (d) students' approaches to learning, and (e) psychosocial contextual influences. They found that performance self-efficacy ($r = 0.59$) was the strongest correlate of GPA, followed by high-school GPA ($r = 0.40$), ACT ($r = 0.40$), and grade goal (the GPA the student intends to attain) ($r = 0.35$).

This study relied mainly on United States samples. As US universities are highly selective, these results may be biased by problems with range restriction, i.e. the predictive value of variables (or their relative importance) may differ in the sample of freshmen that have actually been allowed in tertiary education, relative to the population. Although several methods allow researchers to correct for such bias, these methods are not flawless (Wiberg & Sundström, 2009). The current study is less hindered by restriction of range effects as there are no selection criteria in the higher education system in Flanders, and given that a majority of students also fails the selected program. Moreover, predictions from prior studies do not take into account context-specific differences, such as the specific program for which academic achievement is investigated.

1.3. Differential prediction: disciplinary differences

There is an abundance of studies on academic achievement. Surprisingly, the field of study in which the subjects were recruited is rarely a subject of discussion. Still, the few studies that have addressed this issue show evidence for disciplinary differences in the predictive power of variables. For example, Vedel, Thomsen, and Larsen (2015) studied the variability of predictive power of personality traits (both broad and narrow) across academic majors. They found that the R^2 of Big Five personality facets ranged from 0.16 (Arts/Humanities majors) to 0.57 (Psychology majors). Vanderstoep, Pintrich, and Fagerlin (1996) studied self-regulated learning and found that the relationships between adaptive motivational beliefs and academic performance differed as a function of academic discipline. Shaw, Kobrin, Patterson, and Mattern (2012) found that the relationship between the SAT and GPA varied by major. The SAT was most predictive of GPA in STEM (science, technology, engineering and mathematics) fields. Also, three sections of the SAT differed in their predictive power. SAT-writing tended to be the strongest predictor for most majors, although SAT-mathematics was the strongest for biological and biomedical sciences ($r = 0.59$), engineering/architecture ($r = 0.57$), and mathematics and statistics/physical sciences ($r = 0.59$) majors, while SAT-critical reading was the strongest for security and protective services ($r = 0.55$) majors as well as social services and public administration ($r = 0.55$) majors.

If there is variablity in predictive power between academic disciplines, this has consequences for both counselling (prospective students should be able to evaluate their competences with regard to specific fields of study) and research practice (findings of differential predictive power might also influence the generalizability of results from studies using specific samples in the prediction of academic success). Especially when students do not know yet in which program they are going to enroll, it would be valuable if a common tool that assesses a broad range of academic/cognitive competences allows program specific predictions. As such, a prospective student could use one broad test to evaluate which programs fit his/her personal profile.

1.4. The present study

As stated, studies on the combined predictive validity of a wide range of cognitive and non-cognitive factors are scarce. Thus, a first aim of the current study is to examine the incremental predictive validity of cognitive factors, background variables, personality, self-efficacy, motivation, metacognition and test anxiety in the prediction of academic achievement in a large sample of students having open access to higher education. In doing so, we also test a structural model paralleling the control-value theory of achievement emotions (Pekrun, 2006) in which all variables predict achievement and test anxiety is predicted by motivation and self-efficacy.

In addition to the scarcity of studies on the combination of cognitive, non-cognitive and background factors, the differential predictive validity of these variables across different tertiary education programs is rarely examined. It has been argued repeatedly that different fields of study require different competencies (see e.g., Holland, 1997; Stark & Lowther, 1988). For example, technical fields of study require a higher level of mathematical skills, whereas arts majors require a higher level of verbal skills (Morgan, 1990). Such specificity makes it likely that the predictive power of variables varies across higher education disciplines. If this is the case, prospective students would benefit from the opportunity to evaluate their personal skills with reference to specific fields of study as opposed to receiving generalized feedback on their compentence level. Note that such program-specific prediction is especially challenging on the basis of a common test, for students who are still exploring multiple program options. Surprisingly, few studies have addressed this issue. Yet, findings on differential predictive power of variables across academic disciplines would also have consequences for the generalizability of results from studies using specific samples, and consequently specific academic disciplines, in the prediction of academic success.

In sum, the aim of the current study is twofold:

1. To examine the validity of the combination of background variables, cognitive factors, conscientiousness, metacognition, motivation and test anxiety for the prediction of academic achievement in a sample that is less hindered by restriction of range

Hypothesis 1. In the current sample that is more heterogeneous than student samples that have been pre-selected to attain a tertiary education program, cognitive and background variables will explain a considerable amount of variance in academic achievement across programs.

Hypothesis 2. Conscientiousness, motivation, metacognition and test anxiety will explain variance in academic achievement over and above background and cognitive factors.

Hypothesis 3. The self-efficacy dimension 'effort' will have a positive relation with academic achievement whereas its dimension 'comprehension' will have a negative relation with outcomes.

Hypothesis 4. In a structural model, all variables will predict academic achievement, and test anxiety will be predicted by motivation, self-efficacy and conscientiousness.

2. To examine variations in predictive power of factors across academic disciplines

Hypothesis 5. Program-specific predictions will explain more variance in academic achievement and will lead to higher classification success (i.e., will allow a higher percentage of correctly identified at-risk students) than overall-sample predictions.
Because of the exploratory nature of the current study we have few hypothesis regarding the role of non-cognitive factors in the different study program. With regards to the cognitive factors, we do expect the following:

Hypothesis 6. Verbal skills will be more important in Law and Languages programs as a result of their emphasis on languages.

Hypothesis 7. Mathematical skills will be more important in Psychology and Pharmaceutical sciences as these programs include statistical courses.

2. Method

2.1. Procedure

At the start of the academic year, all new incoming undergraduate students across 5 faculties of Ghent University were invited, both orally and by email, to fill out the instrument. Students who had not completed the instrument by the second week of the academic year received a reminder by email. A second reminder was sent at the end of the second week and the assessment was closed down at the beginning of the third week of the academic year. At the end of the academic year, exam results (both binary pass/fail and GPA) were retrieved from the university database. The study was approved by the faculty ethics committee and students gave written consent for participation.

2.2. Participants

Programs were only considered for inclusion in the study if their response rate was higher than 60% and if there was a minimum of 120 respondents (10 respondents per predictor variable). This led to inclusion of 8 programs of 5 faculties. The overall response rate in these programs was 79%, leaving a sample of 2391 subjects for further analysis. 71.7% of these respondents were female, which is marginally lower than the average number of female students enrolling in the included programs, which is 71.9% (Ministerie van Onderwijs en Vorming, 2014, i.e. Department of Education). 35.8% of the sample passed the first year successfully, which does not deviate from general passing rates in the current study context (Ministerie van Onderwijs en Vorming, 2009). An overview of the included programs and the response rate, gender and passing rate is given in Table 1.

2.3. Measures

An overview of included variables and descriptive statistics for each study program is given in Table 2.

2.3.1. Background characteristics

The hours of mathematics instruction that the respondents received in secondary education was retrieved from the university database.

2.3.2. Cognitive factors

Basic mathematic skills were measured using a 20-item instrument that assesses basic numerical competence, not specific mathematics knowledge. One example item is "Calculate: A book has a 40 % discount and costs €18. What was the price of the book before the discount was subtracted?". Respondents were not allowed to use calculators, but they could use scrap paper to write down calculations. There was no time limit. This instrument has been shown to predict academic achievement in the current study context (Fonteyne et al., 2015). Cronbach α in the current sample was 0.62. Factorial structure was examined using exploratory factor analysis. With the exception of one, all items loaded on one factor. When examining solutions with more factors, these did not indicate multidimensionality of the scale. Therefore, we decided to use the scale as previously validated.

Reading comprehension consists of an English text with 5 multiple choice questions. This text was previously validated and used in the Swedish Scholastic Aptitude Test. Cronbach α in the current sample was 0.32. Internal consistency was low because of the limited number of items and because responses were skewed. Items were answered correctly by most respondents. Yet, as it is the purpose to identify students that lack basic competencies, it is valuable to identify which students fail to answer these questions correctly. All items loaded on one factor.

Vocabulary knowledge was administered with the LexTALE (Lemhöfer & Broersma, 2012). Respondents are asked to indicate whether 60 items (e.g., 'pastitie') are existing Dutch words or not. The resulting percentage score is an indication of general Dutch proficiency ($\alpha = 0.75$). Factorial structure was examined. With the exception of five, all items loaded on one factor. When extracting more factors, these five items did not seem to load on a distinct factor. Therefore, we decided to use the scale as previously validated.

2.3.3. Non-cognitive: conscientiousness

Conscientiousness was measured using the PfPI (De Fruyt & Rolland, 2010), which is a Big Five personality measure that has been validated in the Flemish context. The C-scale consists of 48 items that are rated on a 5-point Likert scale (e.g., I am a well-organised person). Cronbach α was 0.91. All items loaded on one factor.

Table 1
Sample characteristics (response rate, gender and passing rate).

Faculty	Program	Response rate	Sample *N*	% Female	% Passed
Psychology and educational sciences	Psychology	90.2	744	82.4	39.6
Law	Law	90.3	449	61.5	24.3
	Criminology	74.3	135	72.1	23.9
Arts and philosophy	Linguistics and literature	69.9	316	74.4	52.6
	History	67.2	172	33.1	21.2
	Applied linguistics	71.8	147	73.5	33.3
Veterinary medicine	Veterinary medicine	91.6	220	75.5	40.6
Pharmaceutical sciences	Pharmaceutical sciences	82.6	208	78.8	41.3

Table 2
Descriptive statistics of included variables for each study program.

	Psychology		Law		Criminology		Linguistics and literature		History		Applied linguistics		Veterinary medicine		Pharmaceutical sciences	
	M	SD	*M*	SD	*M*	SD	*M*	SD	*M*	SD	*M*	SD	*M*	SD	*M*	SD
Mathematics hours in SE	3.85	1.38	4.10	1.46	3.56	1.20	3.65	1.19	3.78	1.52	3.54	1.07	5.12	1.58	5.50	1.39
Mathematics test	15.41	2.89	14.37	2.42	14.30	2.79	15.58	3.12	14.64	3.79	14.66	2.73	15.85	2.48	18.08	1.95
Reading comprehension	3.53	1.19	3.91	0.99	3.47	1.21	3.83	1.00	3.67	1.13	3.76	1.19	3.67	1.18	3.76	1.17
Vocabulary knowledge	87.60	8.56	89.27	7.40	87.18	9.42	89.69	7.85	89.87	7.53	87.76	9.42	87.75	9.85	87.98	7.73
Conscientiousness	150.15	18.37	157.82	20.91	147.13	16.86	153.70	19.80	144.22	18.14	145.36	20.68	151.02	19.29	151.50	20.67
Test anxiety	52.53	12.42	48.07	12.02	53.12	11.90	48.67	12.64	51.44	13.30	51.78	12.91	50.89	13.12	53.20	13.21
Metacognition (knowledge)	68.56	10.31	72.70	10.04	66.91	10.39	70.29	10.52	65.07	11.62	67.25	11.32	69.60	10.00	69.84	11.67
Metacognition (regulation)	134.49	20.64	141.82	20.66	134.21	20.33	135.53	21.62	127.18	23.06	131.19	22.82	135.75	22.45	137.89	22.56
Controlled motivation	16.45	6.09	16.22	5.95	16.11	5.87	17.65	6.58	16.50	6.14	18.35	6.86	14.77	5.60	17.84	7.03
Autonomous motivation	30.64	4.72	30.85	4.77	29.48	4.67	31.19	4.80	29.79	5.33	29.53	5.29	31.12	4.70	30.58	4.50
Self-eff. (effort)	29.90	4.00	30.69	3.98	29.43	3.75	30.62	3.67	28.48	4.32	29.69	3.96	30.39	3.59	30.61	3.68
Self-eff. (comprehension)	49.78	5.53	51.54	5.94	49.04	5.28	50.60	6.01	48.81	6.72	48.81	6.17	50.65	5.50	51.42	5.39

2.3.4. Non-cognitive: self-efficacy, motivation, metacognition and test anxiety

Academic self–efficacy was measured with an adapted version of the College Academic Self-Efficacy Scale by Owen and Froman (1988). Alpha internal consistency estimates of 0.90 and 0.92 are reported, and the stability across an 8-week period was 0.85. As "social" academic aspects such as "talking to a professor privately to get to know him or her" do not, or only to a lesser extent, apply to undergraduate programs at universities in Flanders, these items were excluded from the original scale, resulting in 22 items. Students used a 5-point Likert scale to indicate their self-efficacy levels. Factor analysis showed that the items loaded on two factors, identified as 'effort' ($N = 8$, loadings between 0.468 and 0.736, e.g., "Attending class regularly", $\alpha = 0.76$) and 'comprehension' ($N = 14$, loadings between 0.416 and 0.636, e.g., "Understanding most ideas you read in texts", $\alpha = 0.79$).

2.3.4.1. Motivation

A Flemish adaptation (Vansteenkiste et al., 2009) of the Academic Self–Regulation Questionnaire (Ryan & Connell., 1989 was administered. Respondents indicated on a 5–point Likert scale to what extent they agree with different reasons for studying. Items for controlled ($N = 8$, e.g., "because I'm supposed to do so", $\alpha = 0.87$) and autonomous motivation ($N = 8$, e.g., "because I want to learn new things", $\alpha = 0.85$) were included. Factor analysis confirmed that items loaded their respective factors (loadings between 0.692 and 0.763 for controlled and between 0.494 and 0.820 for autonomous motivation).

2.3.4.2. Metacognition

The Metacognitive Awareness Inventory (Schraw & Dennison, 1994) was used, which has two main subscales: Knowledge of cognition (17 items, $\alpha = 0.87$, example item "I am good at remembering information") and Regulation of cognition (35 items, $\alpha = 0.93$, example item "I consider several alternatives to a problem before I answer"). As in De Backer, Van Keer, and Valcke (2012), the original scoring system was replaced with a six-point Likert-type scale ranging from 1 (I totally disagree) to 6 (I totally agree). Factorial structure was partially confirmed. Although loadings were below the threshold of 0.40 (Stevens, 2012) for 2 items on the Knowledge of cognition scale and for 4 items on the Regulation of cognition scale, all items loaded on the proposed factor.

Cognitive test anxiety was assessed using the Cognitive Test Anxiety Scale Revised (CTAR) (Cassady & Finch, 2015). The CTAR measures the cognitive domain of test anxiety. Participants responded to 25 items such as "While preparing for a test, I often think that I am likely to fail" using a Likert-scale ranging from 1 to 4. The respondent's total score represents the level of cognitive anxiety. Prior reliability analyses have shown high internal consistency. For example, Cassady (2004) found a Cronbach's alpha of 0.93. In this sample, responses indicated the same high reliability ($\alpha = 0.93$). Unidimensionality of the scale was confirmed with exploratory factor analysis.

2.3.5. Outcome variables

The main dependent variable is whether or not students pass the first year successfully. In Flanders, uniform passing criteria are used across faculties. A student passes the first year when he or she obtains a credit for all courses taken, which means they scored a minimum of 10 out of 20 on the exam. Moreover, assessment methods are fairly uniform in the first year of higher education. In all included study programs, multiple choice and open answer formats are standard. In about 10 to 20% of the courses, these written exams are complemented with coursework and participation credits. This standardization of passing criteria and of examination form allows comparison across study programs. Analyses with GPA (max. 1000) as the dependent variable are also included in order to facilitate comparison with international literature, even though SIMON was designed to optimally predict passing rates at the lower end of study success.

2.4. Analytic procedure

As it is our intention to examine whether a specific cluster of variables significantly adds to the model's ability to predict the probability of passing, we used hierarchical logistic regression (Tabachnick & Fidell, 2007). Although the binary outcome is of specific interest to our study and counselling practice with the instrument, GPA is often used in research on academic achievement. In order to allow for comparison, we also performed hierarchical linear regressions with GPA as the dependent variable. Independent variables entered the regressions in four blocks. The order was based on previous research on academic achievement. First, traditional predictors were entered: educational background first because at the point of assessment, this could not be altered. This was followed by a block of cognitive factors. Next, we included conscientiousness, as this has previously been identified as an important personality variable. To assess the incremental validity of other non-cognitive factors, we entered motivation, self-efficacy, metacognition and test anxiety. Given that SIMON-C is constructed to identify those prospective students who have a very low probability of passing, classification success is also evaluated. These regressions are complemented with a path analysis (with maximum likelihood estimation) in which all variables predict GPA and in which motivation, self-efficacy and conscientiousness predicted academic emotion test anxiety.

3. Results

3.1. Preliminary analysis and descriptive results

Table 2 shows the mean scores and standard deviations for all tests and study programs. Zero-order correlations between variables are reported in Table 3. Prior to analyses, multicollinearity was examined and Variance Inflation Factor (VIF) values were all well below 10 (Stevens, 2012). The residuals histogram showed a fairly normal distribution, which indicated that the normality of residuals assumption was satisfied.

The correlations of test scores with the outcome variables passing and GPA (shown in Table 4) confirmed many of the expected relationships. With few exceptions, background and cognitive predictors were significantly related to the outcome variables, as were the non-cognitive predictors conscientiousness, test anxiety and self-efficacy. There was only one faculty (Arts and philosophy) in which all included predictors were significantly related to academic achievement. In the Veterinary medicine students however, only background and non-cognitive predictors (metacognition, motivation and self-efficacy) were associated with achievement. Contrary to all other programs, cognitive ability predictors, conscientiousness and test anxiety failed to reach significance in Veterinary medicine students.

3.2. Prediction of passing

Table 5 shows the (increase in) explained variance for each cluster of variables (ß's are shown in Table 6). A regression analysis on the total sample yielded significant results for all groups of variables. Background and cognitive variables explained respectively 6 and 8% of the variance in passing which confirmed our first hypothesis. Our second hypothesis, that non-cognitive variables would explain variance over and above traditional predictors, was also affirmed. The explained variance (Nagelkerke R^2) was 0.180. Program-specific analyses generated higher explained variances, varying between 0.179 and 0.282 with an average of 0.233, confirming hypothesis 5.

In seven out of eight study programs, more than one cluster of variables significantly added to the prediction of academic success. In three of the study programs, the motivation and test anxiety cluster was significant (with ΔR^2 between 0.08 and 0.18). In Criminology, this was the only significant cluster. Conscientiousness significantly predicted passing over and above background and cognitive factors in four of the eight study programs (with ΔR^2 between 0.02 and 0.06).

When looking at the significant contribution ($p < 0.05$) of specific variables to the prediction of passing (Table 7), the combination of traditional predictors (cognitive and background factors) and non-cognitive predictors (personality, self-efficacy, metacognition, motivation and test anxiety) allowed for the best prediction in 5 out of 8 programs as evidenced by a significant ΔR^2. For Criminology, Applied linguistics and Veterinary medicine, only non-cognitive variables predicted passing. Supporting Hypothesis 6, we did find verbal skills (reading comprehension and vocabulary) to be important in the Law and Linguistics and literature programs. Yet, contrary to our expectations, these skills did not contribute to the prediction of passing in Applied linguistics. Also, verbal skills significantly predicted passing in the Psychology program. Hypothesis 7 was also partially confirmed. As expected, mathematical skills were important in Psychology and Pharmaceutical sciences, but they were also significant in the Law, Linguistics and literature and History programs.

Hypothesis 3 was confirmed: The self-efficacy dimension 'effort' was only significant in the psychology program, but it was positively related to passing whereas the 'comprehension' dimension had a negative relation with passing in all 4 programs in which it was significant.

3.3. Prediction of GPA

To allow for comparison with the literature, Table 8 shows the variance explained in GPA for each program and for each cluster of variables (ß's are shown in Table 9). A regression analysis using the total sample yielded significant results for all variable clusters, which supported our second hypothesis. The explained variance was 0.171. Confirming Hypothesis 5, program-specific analyses generated higher

Table 3
Zero-order correlations between predictor variables.

	1	2	3	4	5	6	7	8	9	10	11
1. Mathematics hours in SE	–										
2. Mathematics test	0.339**	–									
3. Reading comprehension	0.078**	0.198**	–								
4. Vocabulary knowledge	− 0.122**	− 0.254**	− 0.155**	–							
5. Conscientiousness	− 0.007	0.023	0.038	− 0.008	–						
6. Test anxiety	− 0.025	− 0.076**	− 0.106**	0.026	− 0.265**	–					
7. Metacognition (knowledge)	0.029	0.103**	0.124**	− 0.134**	0.561**	− 0.293**	–				
8. Metacognition (regulation)	0.027	0.092**	0.073**	− 0.165**	0.573**	− 0.123**	0.781**	–			
9. Controlled motivation	− 0.012	0.021	− 0.024	− 0.021	− 0.040	0.240**	0.012	0.046*	–		
10. Autonomous motivation	− 0.018	0.028	0.050*	− 0.038	0.470**	− 0.092**	0.443**	0.471**	0.022	–	
11. Self-efficacy (effort)	0.013	0.049*	0.017	− 0.091**	0.592**	− 0.222**	0.488**	0.490**	− 0.036	0.453**	–
12. Self-efficacy (comprehension)	0.177**	0.226**	0.122**	− 0.095**	0.365**	− 0.348**	0.511**	0.433**	− 0.016	0.374**	0.466**

** $p < 0.01$.
* $p < 0.05$.

Table 4
Correlations of predictor variables with outcomes passing and GPA per faculty.

Faculty	Psychology and educational sciences		Law		Arts and philosophy		Veterinary medicine		Pharmaceutical sciences	
	Pass	GPA	Pass	GPA	Pass	GPA	Pass	GPA	Pass	GPA
Mathematics hours in SE	0.29**	0.29**	0.21**	0.31**	0.12**	0.13**	0.16*	0.17*	0.26**	0.34**
Mathematics test	0.27**	0.27**	0.21**	0.33**	0.21**	0.29**	0.10	0.10	0.21**	0.22**
Reading comprehension	0.22**	0.20**	0.13**	0.14**	0.17**	0.22**	0.07	0.11	0.16*	0.18*
Vocabulary knowledge	0.16**	0.10**	0.12**	0.14**	0.09*	0.14**	0.06	0.08	0.08	0.15*
Conscientiousness	0.12*	0.12**	0.04	0.09*	0.23**	0.27**	0.07	0.07	0.24**	0.26**
Test anxiety	− 0.12**	− 0.12**	− 0.14**	− 0.13**	− 0.22**	− 0.17**	− 0.08	− 0.04	− 0.12	− 0.23**
Metacognition (knowledge)	0.10*	0.10*	0.04	0.04	0.22**	0.25**	0.11	0.12	0.08	0.06
Metacognition (regulation)	0.09*	0.08*	0.02	0.03	0.16**	0.17**	0.14*	0.13	0.10	0.10
Controlled motivation	0.06	0.07	− 0.02	− 0.01	0.10*	0.12**	− 0.01	− 0.01	− 0.02	− 0.02
Autonomous motivation	0.06	0.08*	− 0.00	0.03	0.15**	0.17**	− 0.14*	− 0.06	0.00	0.02
Self-eff. (effort)	0.11**	0.13**	0.03	0.04	0.16**	0.22**	0.16*	0.17*	0.19**	0.24**
Self-eff. (comprehension)	0.07*	0.04	0.10*	0.08	0.16**	0.14**	− 0.01	0.03	− 0.01	0.03

Note. SE = Secondary education; Self-eff. = Self-efficacy.
* $p < 0.05$.
** $p < 0.01$.

Table 5
(increase in) Explained variance of passing for each cluster of variables.

Program	N	R^2 background	ΔR^2 cognitive skills	ΔR^2 Conscientiousness	ΔR^2 motivation and test anxiety	Total R^2
Psychology	744	0.112**	0.087**	0.019**	0.021	0.254
Law	449	0.099**	0.084**	0.003	0.024	0.207
Criminology	135	0.000	0.036	0.006	0.176*	0.218
Linguistics and literature	316	0.012	0.079**	0.059**	0.081**	0.231
History	172	0.026	0.154**	0.003	0.099	0.282
Applied linguistics	147	0.055*	0.024	0.056*	0.097	0.232
Veterinary medicine	220	0.035*	0.016	0.010	0.118**	0.179
Pharmaceutical sciences	208	0.092**	0.080**	0.034*	0.051	0.257
Average		0.054	0.070	0.024	0.083	0.233
Total	2391	0.055**	0.077**	0.018**	0.030**	0.180

Note.
** $p < 0.01$.
* $p < 0.05$.

explained variances, varying between 0.101 and 0.287 with an average of 0.234. In all study programs, except Veterinary medicine, more than one cluster of variables significantly added to the prediction of academic success. In half of the study programs, the non-cognitive motivational/test anxiety cluster was significant (with ΔR^2 between 0.05 and 0.18).

3.4. Classification success

As the aim of the SIMON project is to identify prospective students with very low chances of success, classification success was examined. A new set of regressions were run. First, two logistic regressions were run for each program: one which included the significant variables (shown in Table 7) as identified for prediction of passing in the total sample, and a second regression which included the significant variables for the program specific prediction. Next, the predicted membership (pass/fail) from both regressions was compared to the actual pass/fail in the program, which resulted in a total sample and a program specific classification success rates. Table 10 shows these rates for each program. Classification success was higher for the program-specific prediction ($M = 79.1$) as opposed to the total sample prediction ($M = 76.7$). Thus, using a program-specific prediction, 79.1% of the students that are predicted as failing the program will effectively fail the program, which is 2.4% higher than when using a prediction based on parameter estimates across study programs. This again supports our Hypothesis 5.

3.5. Successful identification of at-risk students

A classification success of 79.1% indicates that 20.9% of the at-risk students would still succeed in passing their first year of studying. Yet, in light of the open access policy it is the ambition of SIMON to minimize false negatives. Therefore, it is important that a classification cut-off is chosen that generates a high sensitivity. Currently a sensitivity of 95% is chosen as acceptable, which corresponds to a maximum of 5% of at-risk students that would unjustly get a warning that their studies are difficult to attain.

Using this 95% sensitivity to select the corresponding cut-off, 3.7% of the failing students were identified as at-risk based on the total sample prediction. In contrast, by using program specific predictions, 13.4% of the failing students could be identified. Table 11 shows these percentages for each program. Thus, using a program-specific prediction more students can be correctly identified as at-risk which again supports our Hypothesis 5.

3.6. Path analysis and structural invariance

To test Hypothesis 4, which implied that all variables would predict academic achievement and that test anxiety would be predicted by motivation, self-efficacy and conscientiousness, we ran path analyses using Lavaan (Rosseel, 2012) in R. Insignificant paths were deleted until a final model was reached. We started with a model in which all variables predicted GPA, and in which self-efficacy, motivational, metacognitive and personality variables predicted the academic emotion test anxiety. First, metacognition was excluded because of insignificance with both test anxiety and GPA, which of course paralleled

Table 6
ß Coefficients of logistic regressions (passing).

Program	Hours of math in SE	Mathematics	Reading comprehension	Vocabulary	Conscientiousness	Test anxiety	Metacognition (knowledge)	Metacognition (regulation)	Controlled motivation	Autonomous motivation	Academic self-efficacy effort	Academic self-efficacy comprehension
Psychology	0.418	0.174	0.380	0.001	0.008	− 0.024	− 0.002	0.005	0.041	0.004	0.065	− 0.049
Law	0.305	0.204	0.263	0.048	0.011	− 0.018	− 0.007	0.001	0.006	− 0.072	0.019	0.009
Criminology	− 0.009	0.094	0.284	− 0.012	− 0.021	− 0.060	0.006	0.006	0.015	0.205	0.010	− 0.116
Linguistics and literature	0.121	0.117	0.339	0.002	0.013	− 0.043	0.017	0.005	0.060	− 0.017	0.033	− 0.035
History	0.201	0.249	0.098	− 0.002	0.018	− 0.023	− 0.040	− 0.011	0.059	0.123	− 0.020	− 0.054
Applied linguistics	0.314	0.043	0.260	0.005	0.016	− 0.045	0.040	− 0.009	0.045	0.044	− 0.091	− 0.007
Veterinary medicine	0.167	0.048	0.090	0.019	− 0.007	− 0.010	0.009	0.023	− 0.010	− 0.131	0.118	− 0.072
Pharmaceutical sciences	0.396	0.340	0.206	− 0.003	0.023	− 0.008	− 0.014	0.007	0.005	− 0.046	0.076	− 0.087
Total	0.238	0.175	0.269	0.002	0.007	− 0.024	0.004	0.002	− 0.006	0.032	0.052	− 0.046

Table 7
Significant variables in the prediction of passing. ($p < 0.05$).

Program	Hours of math in SE	Mathematics	Reading comprehension	Vocabulary	Conscientiousness	Cognitive test anxiety	Metacognition (knowledge)	Metacognition (regulation)	Controlled motivation	Autonomous motivation	Academic self-efficacy effort	Academic self-efficacy comprehension
Psychology	x	x	x			x			x		x	x
Law	x	x		x						x		
Criminology						x				x		x
Linguistics and literature		x	x	x		x			x			
History		x								x		
Applied linguistics						x						
Veterinary medicine										x		x
Pharmaceutical sciences	x	x										x
Total	x	x	x	x	x	x			x		x	x

Table 8
(increase in) Explained variance for each cluster of variables (linear regression with GPA).

Program	R^2 background	ΔR^2 Cognitive skills	ΔR^2 Conscientiousness	ΔR^2 Motivation and test anxiety	Total R^2
Psychology	0.083**	0.056**	0.016**	0.045**	0.201
Law	0.122**	0.088**	0.011*	0.019	0.241
Criminology	0.046**	0.027	0.010	0.181**	0.271
Linguistics and literature	0.020**	0.078**	0.052**	0.062**	0.216
History	0.003	0.173**	0.036*	0.063	0.272
Applied linguistics	0.111**	0.105**	0.038*	0.033	0.287
Veterinary medicine	0.030*	0.014	0.009	0.048	0.101
Pharmaceutical sciences	0.118**	0.058**	0.025*	0.080**	0.280
Average	0.067	0.075	0.025	0.066	0.234
Total	0.049**	0.075**	0.016**	0.031**	0.171

Note.
** $p < 0.01$.
* $p < 0.05$.

findings from previous regressions. Self-efficacy: effort did not predict test anxiety, but motivational factors and conscientiousness did. Autonomous motivation predicted GPA through test anxiety, but not GPA directly. 20% of the variance in test anxiety was explained and 17% of the variance in GPA. The final model with standardized regression coefficients is shown in Fig. 1. The model showed good fit, as indicated by χ^2 (6, 16.43), $p = 0.01$; RMSEA = 0.03 (CI 0.01–0.05), CFI = 0.99 and NFI = 0.98 (Tabachnick & Fidell, 2007).

Next, we tested this final model for structural invariance across study programs. First, this baseline model was applied to each study program separately. Results suggested that the model did not fit all programs equally well (e.g., RMSEA criminology = 0.17). Finally, we conducted a multi-group analysis which involved comparing the baseline model with a second model that is constrained so that the paths are equal between groups. Since we propose that factors differentially predict academic achievement across programs, we expect the model to show structural variance. For model comparisons, we used χ^2 difference tests and looked for changes in RMSEA and CFI. The chi square difference test was significant ($p < 0.001$) and both RMSEA and CFI worsened (from 0.028 to 0.062 and from 0.988 to 0.917 respectively). This again supported our Hypothesis 5 that the parameter estimates varied across study programs.

4. Discussion

The objective of our study was to examine the incremental predictive validity of background, cognitive, personality, metacognitive, self-efficacy and motivational factors for academic achievement in a sample that is less hindered by restriction of range and to study whether this predictive power varies across academic study programs.

As hypothesized, background and cognitive factors were predictive of academic achievement (explaining respectively six and 8% of the variance in passing). Also, for most academic disciplines cognitive predictors and background factors as well as non-cognitive predictors (conscientiousness and self-efficacy/motivation/test anxiety) significantly explained a part of the variance in academic achievement. In three programs (Applied linguistics, Criminology and Veterinary medicine) only non-cognitive factors were predictive of passing the first year.

Although results in the first two mentioned programs may be less stable than those for groups with larger samples, results show that the inclusion of non-cognitive factors allows for better prediction of academic achievement in several programs. For admission decisions, generally only cognitive variables are tested. These variables explain on average 12% of the variance in academic performance (Kuncel & Hezlett, 2010). In the current study, the combination of cognitive with non-cognitive variables explained on average 23% of the variance in GPA and passing, which corresponds to what Robbins et al. (2004) found in their meta-analysis. This increase in explained variance supports the inclusion of non-cognitive variables for orientation and admission decision (see also Kyllonen, 2012). Still, an important counter-indication is that non-cognitive variables, especially when measured through self-evaluation questionnaires and when testing is high stakes, are highly susceptible to socially-desirable responses. This problem is far less manifest when the test is used for study orientation and not for selection purposes, as is the case here, in Flanders. Yet, even in selective environments, non-cognitive variables could increase student success when used post-enrollment for assisting high-risk students (Allen et al., 2009).

The incremental validity of non-cognitive factors for academic performance varied across study programs. The significant variance explained by motivation, self-efficacy and test anxiety factors varied between 2.1% and 17.6%. In comparison, Credé and Kuncel (2008) found incremental variances between 4 and 12% and Robbins et al. (2004) found an increase of 4% over and above traditional predictors.

One may wonder whether an extra 2% in explained variance is meaningful. Allen et al. (2009) recommended to evaluate this in respect to the practical utility of the test scores. A contribution of 2% may be considered relevant when this can aid alleviating academic success and retention, whether this is through adequate study orientation and admission, or through remedial activities after enrolment. The same applies for the increase in classification success of 2.4% based on program specific prediction as opposed to prediction based on total sample parameter estimates. An increase in accuracy by 2.4% is considerable when one deals with prospective students on the verge of a life-altering study choice, especially when the wrong choice implies considerable motivational and financial consequences, both for the individual as for society, in publicly funded education.

Moreover, in line with the ambition of the SIMON project and the open access policy, we chose to minimize the amount of respondents that are falsely identified as risk-student by selecting a classification cut-off that corresponds to a 95% sensitivity. In comparison with a total sample prediction and cut-off, 9.7% more failing students were correctly identified as being at-risk using program-specific predictions.

The variability in predictive power across study programs was also confirmed by testing a path model of relations between variables. We first tested relations as proposed in the control-value theory of achievement emotions (Pekrun, 2006). In support of this model, we did find that all variables (except metacognition) predicted GPA. Also, achievement emotion (in this study test anxiety) was influenced by motivation and by the comprehension dimension of self-efficacy (but not the effort dimension). In addition to the Pekrun model, we found that test anxiety was also affected by conscientiousness. Confirming our hypothesis of variability across study programs, the final model showed structural variance. This indicates that the structural relationship between variables differed depending on the study program. Future studies could focus more on this variability. Several authors have argued that student performance is multidimensional (Kuncel,

Table 9
Standardized ß coefficients of linear regressions.

Program	Hours of math in SE	Mathematics	Reading comprehension	Vocabulary	Conscientiousness	Test anxiety	Metacognition (knowledge)	Metacognition (regulation)	Controlled motivation	Autonomous motivation	Academic self-efficacy effort	Academic self-efficacy comprehension
Psychology	0.245	0.191	0.152	0.036	0.064	− 0.145	0.001	0.014	0.116	0.037	0.135	− 0.166
Law	0.256	0.212	0.103	0.131	0.165	− 0.080	− 0.043	0.015	0.030	− 0.118	0.044	− 0.069
Criminology	0.203	0.136	0.093	− 0.005	− 0.121	− 0.123	0.148	− 0.025	0.035	0.463	− 0.019	− 0.278
Linguistics and literature	0.124	0.232	0.160	0.094	0.165	− 0.210	0.054	− 0.029	0.128	− 0.001	0.118	− 0.219
History	0.046	0.271	− 0.027	− 0.245	0.197	0.021	0.151	− 0.281	0.189	0.103	0.051	− 0.037
Applied linguistics	0.242	0.175	0.212	0.136	0.135	− 0.171	0.122	− 0.084	0.054	0.093	− 0.017	− 0.121
Veterinary medicine	0.142	0.071	0.067	0.055	− 0.042	0.032	0.100	0.087	− 0.028	− 0.160	0.194	− 0.124
Pharmaceutical sciences	0.261	0.145	0.074	0.115	0.146	− 0.221	− 0.249	0.117	0.075	− 0.087	0.202	− 0.168
Total	0.170	0.257	0.119	0.121	0.065	− 0.116	0.025	− 0.018	0.093	0.029	0.124	− 0.160

Table 10
Successful classification of failing students based on total sample parameter estimates versus based on program specific parameter estimates.

	Successful classification of failing students for prediction across study programs	Successful classification of failing students for program specific prediction
Psychology	77.4	79.5
Law	85.9	81.6
Criminology	79.4	83.5
Linguistics and literature	65.6	75.8
History	86.7	84.7
Applied linguistics	70.4	79.8
Veterinary medicine	66.7	71.2
Pharmaceutical sciences	81.1	76.5
Total	76.7	79.1

Table 11
Percentage of students correctly identified as risk-students based on total sample versus based on program specific prediction with a cut-off at a sensitivity of 95%.

	% of failing students that is correctly identified based on total sample prediction with a cut-off at 95% sensitivity	% of failing students that is correctly identified based on program specific prediction with a cut-off at 95% sensitivity
Psychology	3%	6.2%
Law	3.5%	26.5%
Criminology	9.8%	26.5%
Linguistics and literature	2.7%	6.8%
History	4.2%	17.6%
Applied linguistics	5.1%	1.4%
Veterinary medicine	3.8%	3.1%
Pharmaceutical sciences	1.6%	18%
Total	3.7%	13.4%

Hezlett, & Ones, 2001; Oswald, Schmitt, Kim, Ramsay, & Gillespie, 2004). It would be interesting to thoroughly examine how and why the explanatory value of these dimensions varies by major.

Although their predictive power varied across study programs, most variables did, as expected, significantly contribute to the prediction of academic performance. Cognitive ability, conscientiousness and test anxiety predicted academic achievement in all programs, with the notable exception of Veterinary medicine. In this program, only autonomous motivation and self-efficacy (comprehension) significantly predicted passing, and both did so negatively. Several studies have emphasized that non-cognitive constructs are critical for success in veterinary medicine (see e.g., Lewis & Klausner, 2003). Our study seems to support this claim. The negative relation between autonomous motivation and academic success is somewhat contrary to expectations, but not completely incomprehensible. Ilgen et al. (2003) found that one of the strongest motivators for choosing a career in veterinary medicine was having a pet. Although testifying of autonomous motivation, having a pet does not seem the most solid basis to succeed in an educational program. Especially not when this is combined with a restricted knowledge of the veterinary profession, which was also found by the authors, even in their selective study context. An alternative explanation is that autonomously motivated students neglect boring topics in favor of preferred ones which jeopardizes their exam performance (Senko & Miles, 2008).

The negative relation between self-efficacy (comprehension) and achievement was not a surprise and was also found in other programs. The two dimensions of self-efficacy predicted achievement differently

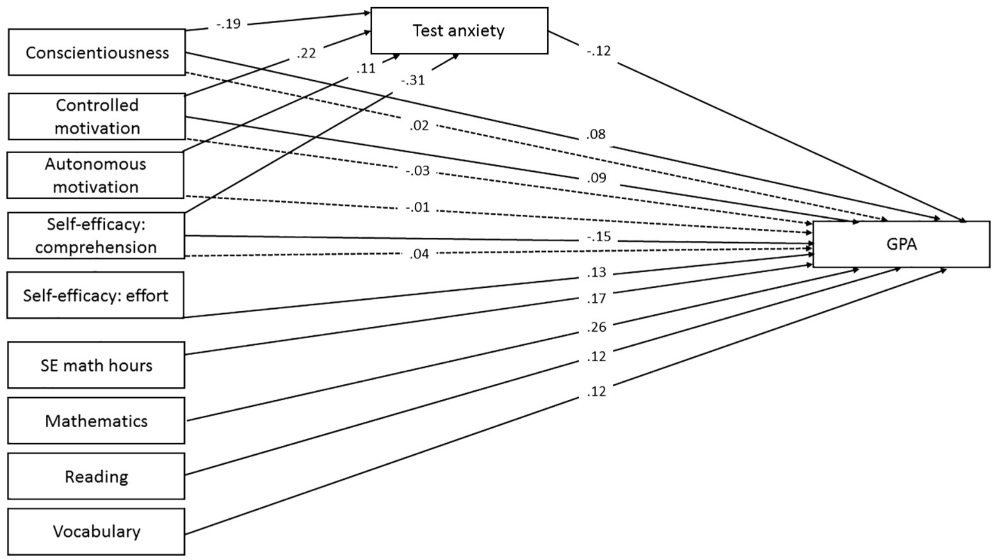

Fig. 1. Path model with standardized estimates. Only significant paths are shown. Full lines indicate direct, dotted lines indirect effects.

with the comprehension dimension having negative effects, whereas the dimension of effort showed a positive relation with achievement. This is in line with Vancouver and Kendall (2006), who reason that high self-efficacy can lead to diminished effort which negatively affects performance. Our results show that it may be important to distinguish effort from comprehension when discussing academic self-efficacy, with the latter including a potential risk to overestimate one's personal abilities. Future studies need to look into this further.

Only one variable, metacognition, failed to contribute to the prediction of academic achievement in all of the study programs, similar to Kitsantas et al. (2008) and Sperling, Howard, Staley, and DuBois (2004). One possible explanation is that this is a measurement artefact. Metacognition was administered using a self-evaluation questionnaire, while Veenman, Van Hout-Wolters, and Afflerbach (2006) showed that scores on questionnaires hardly correspond to actual behavioral measures of metacognition during task performance. Think-aloud-protocols would be an alternative, but these are time-consuming and difficult to include in an online assessment.

Most participants in studies on prediction of academic achievement have previously been selected for admission using admission tests, often heavily relying on intelligence tests (Sedlacek, 2011). Therefore, results need to be corrected for range restriction effects. In the current study, subjects have not been subjected to an admission process since all included academic study programs are open to any student who has a secondary education qualification. Moreover, the fact that a majority of students also fails the enrolled program illustrates that incoming students have more heterogeneous cognitive abilities than most US samples. Yet, there is definitely a self-selection process. Of all secondary education graduates, about 63% attend tertiary education and 60% of these students enroll in an academic study program (Van Daal, Coertjens, Delvaux, Donche, & Van Petegem, 2013). The current results hence speak only for students who enter higher education in a completely open system, but not for the entire population per se.

The current study also has some limitations. First, although research has shown that especially conscientiousness is incrementally predictive of academic performance (Conard, 2005; de Koning et al., 2012; Farsides & Woodfield, 2003; Noftle & Robins, 2007; Poropat, 2009; Trapmann et al., 2007; Trautwein, Ludtke, Roberts, Schnyder, & Niggli, 2009) other (Big Five) personality traits were not included in the study. Vedel et al. (2015) already showed how the predictive validity of personality traits differs across study programs. Future research should examine the differential and incremental validity of other personality traits. Second, apart from personality, inclusion of other variables might augment prediction accuracy. Although 23% of variance in academic achievement was accounted for, a lot remains unexplained which calls for inclusion of other constructs. To name but a few, self-control (see e.g., Tangney, Baumeister, & Boone, 2004) and other motivational constructs such as the utility value of the course (Eccles & Wigfield, 2002) have been shown to predict academic achievement. It may also be worthwhile to examine academic emotions other than test anxiety, both positive and negative, such as enjoyment or boredom (Detmers et al., 2011; Pekrun, Goetz, Titz, & Perry, 2002). Including these and other factors may allow a better prediction and thus a more comprehensive model of (program-specific) academic achievement. Third, although a range of programs were included in the current study, STEM (Science, technology, engineering and mathematics) programs were not. Future studies should test whether similar cognitive and non-cognitive constructs predict academic success in STEM areas or whether it is more beneficial to rely on more program specific knowledge. Finally, only first year academic success was predicted. Although it has been documented that first year results are powerful predictors of overall academic achievement (de Koning et al., 2012) and college retention (Allen, 1999), follow-up studies should examine whether the results hold as to timely graduation and other performance indicators.

The current study has several practical implications. The fact that non-cognitive factors have incremental predictive validity for academic outcomes over and above cognitive abilities has repercussions for admission decisions. Where possible, they should be used in admission processes and especially in study orientation. During this orientation phase, it is in the interest of the prospective student to answer honestly during non-cognitive assessments, as this would generate the most suitable advice. As such, social desirability issues stemming from non-cognitive self-tests are diminished. Indeed, the current study showed that it is possible to use self-evaluation questionnaires in an online format to assess self-regulation and motivational variables and that scores on these measures increase prediction accuracy. These assessments are relatively cheap, especially compared to labor-intensive selection procedures that intend to capture these variables such as carrying out interviews and screening letters of recommendation or essays. Therefore, it may be worthwhile to examine whether they would hold in selective contexts. In any case, they seem suitable to include in self-assessment instruments for study orientation and for prediction of academic achievement such as SIMON. The use of instruments that assess personal abilities and the fit with educational programs can be an important leverage to increase student retention. At the very least, it enables an informed choice. In a system with open access to virtually all majors, this should encourage students to choose a program that maximizes their chance of success.

The inclusion of non-cognitive variables also opens possibilities for institutions. It allows the use of test scores for the identification of students at risk of academic failure and it facilitates the design of interventions. For example, research has shown that self-regulation training interventions can increase academic performance (Credé & Kuncel, 2008). Self-efficacy and motivation interventions can also be implemented by higher education institutions (Kitsantas et al., 2008).

The differential predictive validity of specific cognitive and non-cognitive factors across study programs also has implications for research and for counselling. Shaw et al. (2012) suggested that this variability across programs might be a consequence of the nature of the course work by major, the academic "culture" of the different majors (e.g., male-dominated or highly competitive) and of differences in grading practices. In the current study, the nature of the course work and the passing criterion were fairly uniform across programs, but more research is definitely needed on the reasons for differential predictive validity.

In anticipation of future research, investigators should be aware of the limitations of the use of subjects from specific fields of studies in predicting academic outcomes. Study samples are often constituted by psychology students as these are a convenient sample to many scholars in this research area (Busato et al., 2000; Cassady & Johnson, 2002; Chamorro-Premuzic et al., 2006; de Koning et al., 2012; Harackiewicz, Barron, Tauer, & Elliot, 2002; Komarraju & Nadler, 2013; Ridgell & Lounsbury, 2004; Ziegler, Knogler, & Buehner, 2009, to mention but a few). Many studies do not even mention the specific major of their participants (e.g., Farsides & Woodfield, 2003), or do not take this information into account when interpreting study results (Chapell et al., 2005). Therefore, researchers should replicate findings across student populations and they should at least mention the specific study program their subjects were taken from and limit their conclusions to this program.

As for career counselling, test results should always be interpreted in light of a specific study program, and not only with regards to the study level. This study shows that although a uniform test battery is used, it is possible and valuable to make context specific predictions.

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