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Basic mathematics test predicts statistics achievement and overall first year academic success

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Abstract In the psychology and educational science programs at Ghent University, only 36.1 % of the new incoming students in 2011 and 2012 passed all exams. Despite availability of information, many students underestimate the scientific character of social science programs. Statistics courses are a major obstacle in this matter. Not all enrolling students master

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the basic mathematical skills needed to pass statistics courses. Therefore, we propose a test that measures these skills. Our aim is to examine the predictive validity of the test with regard to the statistics course and also as to overall academic success. The results indicate that a test of very basic mathematics skills helps identify at-risk students at and before the start of the academic year. The practical implications of these results are discussed. The test aids the efficient use of means for remedial interventions and supports future students in choosing a higher education program that suits their potential.

Keywords Prediction · Academic success · Basic mathematic skills · Statistics · Passing

Introduction

Success rates in higher education are low. The Organization for Economic Co-operation and Development reported that at this level (over 19 OECD countries) 31 % of tertiary education students failed to complete a program (OECD and Indicators 2008). Moreover, the costs of student dropout are high. For example, the Flemish governments' average annual cost per student is $16,000 (Cantillon et al. 2005). Therefore, governments, institutions, and students are in search of factors that can help determine whether someone will pass or not. Attrition problems are manifest worldwide, but the open access policy of the Flanders educational system poses additional challenges. Therefore, before discussing the determinants for academic achievement in the literature, a short framing of the specific Flemish educational context is in order.

The Flanders education system: structure and admission

There are four types of secondary education (SE) programs in Flanders. The first, general SE (GSE), has an emphasis on broad general education and provides a solid foundation for higher education. Second, technical SE (TSE) emphasizes general and technical matters and prepares for a profession or to still pass on to higher education, which is less frequent. Third, secondary arts education (ASE) combines a broad general education with active arts practice. Finally, vocational SE (VSE) is a practice-oriented education in which young people learn a specific profession (Education in Flanders 2008).

Flemish higher education could be described as binary (Arum et al. 2007). It consists of two main types of programs: academic and professional. Academic programs are mainly organized by universities, whereas university colleges provide professional programs with an emphasis on executive skills. The professional programs lead to a bachelor degree and correspond to the Bologna first cycle programs of 180 European Credit Transfer and Accumulation System (ECTS) (The Bologna Declaration 1999). Academic programs also lead to a bachelor degree at first, but the finality is to complement this degree by a master. Academic programs thus correspond to the Bologna two-cycle programs (for a detailed description of the higher education system in Flanders, we refer to Kelchtermans and Verboven (2008)).

Although some SE programs do not typically prepare for higher education, students can enter almost all tertiary education programs when they obtained a degree from any of these four SE programs. There is no *numerus clausus*, there are no requirements on the grades obtained during SE for access to higher education, and there are, with the exception of medical and artistic programs, no entrance exams. Moreover, there is a policy of high subsidies and very low tuition fees (Kelchtermans and Verboven 2008), which are typically less than $800/year.

These measures aim to guarantee socially fair access and improve participation in higher education but have the disadvantage that the first year of university is typically a "selection year." In general, after 1 year of studying, not even half of the newly enrolled students pass (Rombaut 2006). As mentioned, this implies a high cost for students, parents, institutions, and the government (Declercq and Verboven 2010).

Educational background and student success

Because the system is open to anyone who has completed SE, virtually all programs show a large heterogeneity in SE backgrounds of new incoming students. For example, the amount of mathematics instruction in SE varies between 0 (in VSE programs) and 8 h (in some GSE programs) per week. This heterogeneity is reflected in the differences in passing rates, especially in academic bachelor programs which have a focus on research and scientific skills and knowledge. Students with a VSE degree are consistently less successful than those with a general degree, with success rates of students with technical and arts degrees fluctuating between these extremes. (Declercq and Verboven 2010; Rombaut 2006; Studiesucces Generatiestudenten 2007; Studievoortgang bij generatiestudenten 2012). Even within the group of students with a general secondary degree, there are major differences in higher education success rates. Students with a general degree focusing on classical languages, mathematics, and science tend to outperform students with a general degree that focuses on modern languages or social sciences.

The average success rate of newly enrolled students at the Faculty of Psychology and Educational Sciences of Ghent University (during the academic years 2005–2006 to 2008–2009) is 49.5 % (Studievoortgang bij de generatiestudenten aan de Universiteit Gent 2012). During the academic years 2011–2012 and 2012–2013, only 36.1 % of these new students passed all exams successfully. So, rates are dropping.

One of the contributing factors to these low success rates is a suboptimal knowledge of what academic programs entail. Many students seem to underestimate the scientific character of programs in the social sciences. Especially statistics courses are a major obstacle in this matter. For example, Murtonen and Lehtinen (2003a, b) showed that social science students rated statistics courses as the most abstract and difficult subject. Many of these students felt that they were non-mathematical persons and as such could not learn mathematical subjects. Some students were even convinced that no relevant information in human sciences can be obtained through quantitative methods.

On the other hand, educational background does not explain completely why some students pass and others do not. For example, a lot of students succeed despite the fact that they come from SE programs that do not prepare them specifically for (academic) tertiary education. This might be the result of the fact that not only cognitive factors contribute to the choice of SE schooling, but also social class (Werfhorst et al. 2003). Hence, the obtained secondary degree does not always reflect the ability of students to cope with the requirements of academic programs in general and the statistics courses specifically. So, there is a clear need not only in students, but also in student counselors and educators for information about students' initial competences and chances of success.

Statistics courses in the social sciences

Most graduate students enrolled in social and behavioral sciences programs worldwide are required to take at least one statistics course and/or a quantitative-based research methodology course as part of their program (Onwuegbuzie 2003a, b). It is widely acknowledged that statistics and quantitative methods courses cause problems (Murtonen and Lehtinen 2003a, b), especially for students in social sciences, who generally have less interest and schooling in mathematical subjects. As a result, factors related to success in statistics courses have been the subject of research.

As Lalonde and Gardner stated (1993), most of the variables that have been examined regarding the acquisition of statistical knowledge fall within three broad categories: anxiety, attitudes, and ability.

Several scholars have addressed the influence of attitudes toward statistics (Budé et al. 2007; Cashin and Elmore 2005; Chiesi and Primi 2010; Gal and Ginsburg 1994; Schau et al. 1995). The general conclusion of these studies is that more positive attitudes relate to better exam results (Vanhoof et al. 2006). The negative impact of statistics anxiety on performance has also been widely documented (e.g., Chiesi and Primi 2010; Macher et al. 2011; Mellanby and Zimdars 2010; Musch and Bröder 1999; Vigil-Colet et al. 2008).

In this study, we will focus on the third category: ability. Both very specific abilities, such as spatial visualization ability (Elmore and Vasu 1980) and general abilities, such as intelligence, have been examined in relation to statistics achievement. Numerous studies have demonstrated a strong positive correlation between general intelligence and educational outcomes (Kuncel et al. 2004). In the current study, the primary concern was that seeing the influx of students with very dissimilar backgrounds, not all enrolling students master the basic mathematical skills needed to pass statistics courses and perhaps also to pass many other courses that rely on empirical evidence and research. Mathematic ability is therefore the primary variable of interest in the current study.

A few earlier studies have already addressed the importance of mathematical skills for achievement in statistics courses (Chiesi and Primi 2010; Harlow et al. 2002; Lalonde and Gardner 1993; Schutz Paul et al. 1998). Garfield and Ahlgren (1988) pointed out that one of the reasons that students have difficulties grasping the fundamental ideas of probability is the fact that many students have underlying difficulties with rational number concepts and basic concepts involving fractions, decimals, and percentages.

Mathematical skills have often been operationalized by previous mathematical achievement (e.g., Musch and Bröder 1999; Onwuegbuzie 2003a; Tremblay et al. 2000; Wisenbaker et al. 2000). Others have constructed tests to measure mathematical skills (Harlow et al. 2002; Lalonde and Gardner 1993; Schutz et al. 1998). More recently, Galli et al. (2011) and Johnson and Kuennen (2006) have created a specific test measuring basic mathematics skills. Both studies provide evidence of the significant contribution of these skills to predict results on statistics exams. Galli et al. (2011) found that students with low mathematical ability had significantly lower grades than students with a medium-high ability. Johnson and Kuennen (2006) found that students who answered all basic mathematics questions correctly were likely to earn a half to a full letter grade higher in an introductory business statistics course. Consequently, they raised the question whether basic math skills may be more important than previously recognized. Ballard and Johnson (2004) came to a similar conclusion with regard to an introductory microeconomics course. They found mastery of extremely basic quantitative skills to be the most important factor for course success, even more than American College Testing (ACT) math scores.

None of these studies, however, examined the extent to which these measures discriminate between students passing their first year successfully and those who did not. In social sciences programs at Ghent University, passing the first year is closely associated with passing the statistics exam: 85.3 % of the students that did not pass the first year also failed the statistics exam. Since passing the statistics course is required to pass the first year, none of the students failing the statistics course passed the first year. Of the students that pass the statistics course, 79.2 % passes the first year. Seventeen percent of the failing students pass all courses except the statistics course (there are 12 courses in the standard package of 60 ECTS credits). In other settings as well, students have been reported to view statistics courses as a major threat to the attainment of a degree (Onwuegbuzie 1995). For many students at least, this seems to be not far from the truth.

From success in the statistics course to overall academic success

Observing the generally acknowledged relation between performance in statistics courses and general academic achievement in social science programs, it is surprising that studies examining this relation are, to our knowledge, non-existent. Math subscales of standardized tests (e.g., Scholastic Aptitude Test and ACT) link mathematical ability to academic achievement, but they might lack the specificity to assess mathematical ability necessary for statistics courses in non-mathematical majors (Galli et al. 2011). If basic mathematical skills contribute to the variance in statistics achievement and if there is a high correlation between statistics achievement and general achievement, the question rises whether a basic mathematics test can contribute to the prediction of general academic achievement.

Our aim was to propose and validate an easy-to-administer test that measures basic mathematical skills considered vital to successfully take on an introductory statistics course in an academic bachelor program. This test was therefore not primarily aimed to discriminate between the better performing students. Because of the heterogeneity of new incoming students and the lack of standardized testing in the Flemish education system, this test could especially help identify at-risk students. In addition, we examined to what extent basic mathematical skills predict overall academic success. To further substantiate this, we examined the relation between the mathematics test and success in non-mathematical courses. As such, this test may offer a valuable tool in the choice of a major in tertiary education.

To summarize, our goal was twofold:

1. Determining whether a basic mathematics test can predict academic achievement in statistics over and above SE background. Can we predict who will pass the statistics exam?
2. Determining whether a basic mathematics test can predict general academic achievement over and above SE background. Can we predict who will pass the first year successfully? To further substantiate this, analyses of success in non-mathematical courses are added.

Method

Instruments

Construction of the mathematics test: construct definition and item generation To construct the mathematics test, two matters were considered: the mathematical skills that students are supposed to have acquired by the end of SE as described by the Department of Education in Flanders ("Vakgebonden eindtermen derde graad secundair onderwijs-ASO") and the mathematical prerequisites for the introductory statistics course in the bachelors of psychology and educational sciences. The latter were evaluated by teachers and experts in the field of statistics and by faculty guidance counselors who had been administering informal tests of basic mathematical skills to first year students since 2 years.

A pool of items was developed reflecting basic numerical mastery to be achieved after SE and reflecting prerequisites to enroll the introductory statistics course. These items can be subdivided in seven mathematical topics: numerical knowledge and the order of operations, operations with decimal numbers, operations with brackets, operations with fractions, algebra: working with unknown variables, percentages/proportions, and the rule of three. One example question is “If a runner runs on average 1 km in 5 min, how many has he run after 2 h?” (see Appendix for full 20-item scale). Question format was varied. Open questions, yes/no items, and multiple-choice questions were alternated.

Reliability analysis of the currently studied sample showed a Cronbach’s alpha of .76, which shows that scores on the mathematics test were fairly reliable (Field 2009). This coefficient is acceptable according to recommendations set forth for preliminary and basic research, and it is in line with the mean .77 alpha reported in previous studies (Peterson 1994).

To avoid cheating, the test was constructed in four different versions in which the sequence of items was varied. To guarantee comparability, the effect of item sequence was checked. An analysis of variance test shows that test scores did not differ across test versions ($F(3,1935)=0.06$, $p=.98$). Hence, all versions were aggregated for further analysis.

Background variables Information on the background variable SE diploma and number of hours of mathematics instruction in SE was obtained from the university database. Students were asked to give this information when enrolling for the first time at Ghent University.

Achievement measures The academic year in Flanders starts at the end of September and consists of two semesters. At the end of each semester, exams are organized that cover the courses taken during the past semester. This gives students a first chance to prove that they have acquired the contents of each course. In Flanders, grades in higher education vary between 0 and 20, with a score of 10 as the passing criterion. If a student does not obtain a score of 10 or higher for the taken courses, he or she gets a second chance to pass the exam. Thus, students get two attempts at passing each course during one academic year.

Grades were obtained from the university database. “Statistics score” is the grade obtained in the introductory statistics course irrespective of the amount of chances taken on the exam. Statistics achievement was further operationalized as “passing statistics” (a dichotomous variable that indicated whether a student obtained a grade of 10 or higher or not). Results on two non-mathematical courses were also analyzed. The introductory psychology course (“passing psychology”) and the sociology course (“passing sociology”) were selected because of their inclusion in both the psychology and the educational science program because these are not methodological or statistical and are introductory courses in the field of study that students signed up for. The contents should therefore be closely aligned to the students’ interests.

General achievement was operationalized as “general success rate (GSR)” which is the ratio of the number of credits that a student obtained over the number of credits that he or she subscribed for. Thus, a GSR of 100 means that the student passed all enrolled courses. This rate was further dichotomized as “passing the first year” (yes or no).

Data collection

The paper-and-pencil test was administered in the second week of the academic year during the introductory statistics class. The advantages of this early administration were threefold. First, in the second week of the academic year, dropout was non-existent or at least very low. Secondly, class attendance decreases as the semester advances (Van Blerkom 1992). Thirdly, as the semester advances, students gain knowledge and skills that might bias our measures of initial competence and, therefore, confound predictive validity. Thus, assessments early in the semester positively impacted the response rate, and results on the mathematics test were less contaminated by skills and knowledge gained throughout the academic year. All students attending the class were asked to fill out the test, and they were informed that results would be used only for research purposes.

Participants

In the academic years 2011–2012 and 2012–2013, 1,278 new students enrolled at the Faculty of Psychology and Educational Sciences. Of these students, 80.9 % filled out the mathematics test, so responses of 1,034 students were analyzed. Eighty seven point two percent of the sample were females. The proportion of female students is traditionally high in these majors, but this sample proportion was slightly higher than the proportion of female first-generation students (84.6 % in the academic years 2011–2012 and 2012–2013). Ninety seven point three percent of the sample was enrolled in the standard package of 60 ECTS credits.

Procedure

First, several *t* tests were carried out to determine whether the samples 2011–2012 and 2012–2013 differed significantly with regard to the dependent and independent measures. Next, we examined whether there was a significant relation between the test score and the outcome variables (passing statistics, passing psychology, passing sociology, and passing the first year) through correlational analysis and *t* tests. Third, we conducted a preliminary analysis to determine whether the main outcome variables differed as a function of several background variables. If so, these variables were included in logistic regression analysis to determine whether our mathematics test could improve prediction of outcome above and beyond these background variables. Finally, sequential logistic regression was used to determine whether our mathematics test helped in the prediction of the outcome variables.

Results

Cohort comparison

To determine whether the cohorts of 2011–2012 and 2012–2013 differed significantly on the dependent and independent variables, independent *t* tests were carried out.

The *t* tests showed that there were no significant differences in passing the first year between students from the 2011–2012 cohort (M=.42, SD=.49) and those from the 2012–2013 cohort (M=.38, SD=.49) ($t(1{,}027)=1.28$, $p=.20$). There were no significant differences in passing the statistics course ($t(1{,}025)=-.68$, $p=.50$), in passing psychology ($t(1{,}024)=.01$, $p=1$), or in passing sociology ($t(1{,}011)=1.66$, $p=.10$) between students from the 2011–2012 cohort (M=.48, SD=.50; M=.77, SD=.42 and M =.68, SD=.47, respectively) and those from the 2012–2013 cohort (M=.50, SD=.50; M=.77, SD=.42 and M=.63, SD=.48, respectively). Cohort 2011–2012 (M=3.54, SD= 1.68) and cohort 2012–2013 (M=3.60, SD=1.50) did not differ with regard to the hours of mathematics instruction in SE ($t(878)=-.53$, $p=.60$). Mathematics test score differences were also insignificant ($t(1{,}032)=.77$, $p=.44$) between cohort 2011–2012 (M=14.85, SD=3.55) and cohort2012–2013 (M=14.68, SD=3.30).

These tests indicated that there were no significant differences in outcomes, features, or test responses between cohorts. Thus, we felt safe to aggregate the data for further analyses.

Descriptive statistics and bivariate correlations

Descriptive statistics of the mathematics test scores Scores on the mathematics test varied between 2 and 20 with a mean score of 14.77 (SD=3.44). Skewness was −.57 (SD=.08). Taking the rule of thumb that a skewness value more than twice its standard error indicates a departure from symmetry (De Laurentis et al. 2010), scores on the mathematics test were negatively skewed. This might indicate a ceiling effect, resulting in worse discrimination at the high end of the scale, which is plausible as the test aimed only to assess basic starting-level competences. Kurtosis (−.16) was less than twice its standard error (.15), indicating that the test scores did not significantly differ from mesokurtic distribution.

Descriptive statistics and correlational analysis Table 1 provides descriptive statistics of other variables measured and included in the analysis. For all continuous variables (mathematics test score, statistics score, GSR, and hours of mathematics in SE), Pearson correlations are given. Point biserial correlations (r_{pb}) are shown for the dichotomous outcome variables. The statistics course was passed by 48.8 % of the sample, the psychology course by 76.7 %, the sociology course by 64.2 %, and the first year successfully by 40 %.

An independent sample t test showed that students passing the statistics exam scored significantly higher on the mathematics test (M=16.15, SD=2.96) than students not passing the statistics exam (M=13.44, SD=3.35) ($t(1{,}025)=-13.75$, $p<.01$). Significant differences in math test score were also found between students passing (M=15.25, SD=3.23) and failing (M=13.11, SD=3.64) the psychology exam ($t(1{,}024)=-8.66$, $p<.01$) and students passing (M=15.39, SD=3.16) and failing (M=13.60, SD=3.68) the sociology exam ($t(1{,}011)=-7.73$, $p<.01$). Students passing the first year successfully also scored significantly higher on the mathematics test (M=16.16, SD=2.92) than those who did not (M=13.86, SD=3.45) ($t(1{,}027)=-11.55$, $p<.01$).

Figure 1 shows passed-failed distribution as a function of mathematics test score.

Since both mathematics test score and hours of mathematics instruction in SE correlated with passing the statistics course and passing the first year, partial correlations were computed between mathematics test score and these outcome variables, controlling for hours of mathematics instruction. The results suggested that the mathematics test score was related to both passing the statistics course ($r=.31$, $p<.01$) and passing the first year ($r=.24$, $p<.01$).

Moreover, analysis using Steiger's Z tests revealed a stronger relation between mathematics test score and achievement measures (.43, $p<.01$ for statistics score and .35, $p<.01$ for GSR) than between the number of hours of mathematics instruction in

Table 1 Descriptive statistics and correlations

Variable	Mean	SD	Math test score	Statistics score	GSR	Hours of math in SE	Passing statistics	Passing Psychology	Passing Sociology	Passing the first year
Math test score	14.77	3.44	1.00	.43**	.35**	.37**	.39** r_{pb}	.26** r_{pb}	.25** r_{pb}	.33** r_{pb}
Statistics score	7.70	5.10		1.00	.75**	.32**	.81** r_{pb}	.55** r_{pb}	.53** r_{pb}	.71** r_{pb}
GSR	71.42	33.18			1.00	.23**	.73** r_{pb}	.76** r_{pb}	.71** r_{pb}	.71** r_{pb}
Hours of math instruction in SE	3.44	1.72				1.00	.28** r_{pb}	.19** r_{pb}	.11** r_{pb}	.26** r_{pb}

GSR general success rate, *SE* secondary education, r_{pb} point biserial correlation

**Correlation is significant at the 0.01 level (two-tailed)

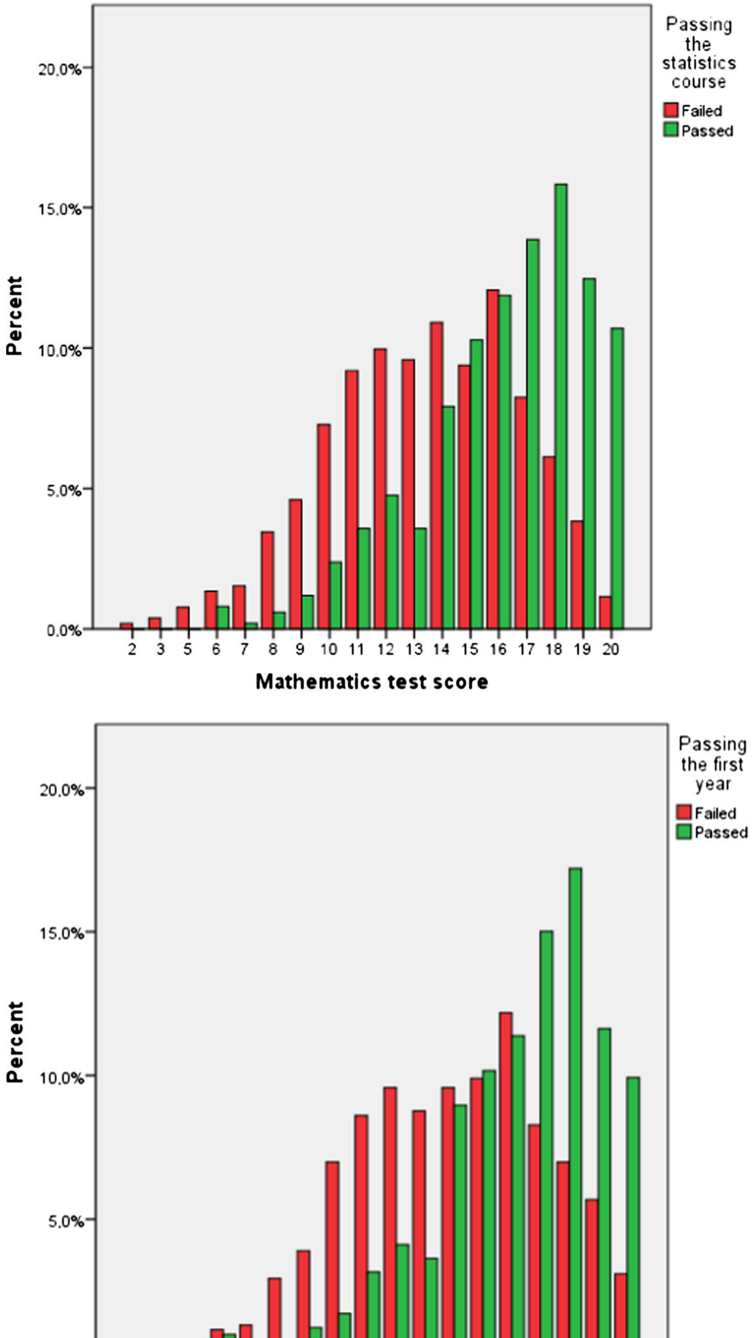


Fig 1 Distribution of mathematics test scores and passed-failed categories of the statistics course (*top*) and the first year (*bottom*)

SE and achievement measures (.32 and .23 respectively, $p<.01$) ($Z=2.61$, $p<.01$ for passing statistics and $Z=2.71$, $p<.01$ for passing the first year). This was promising, as it might suggest that the mathematics test is more predictive for achievement than educational background.

Preliminary analysis of background variables

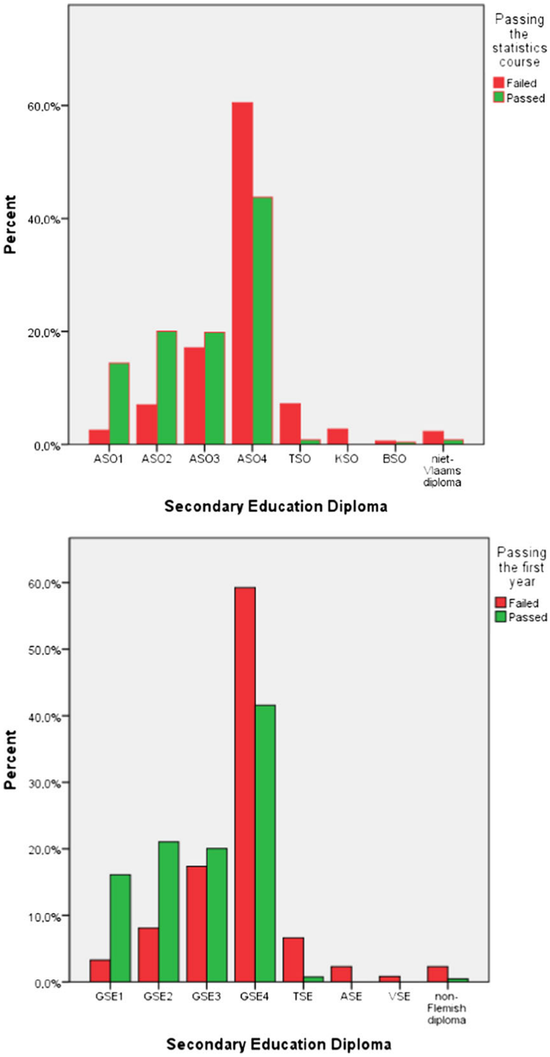
Preliminary analyses were conducted to determine whether the outcome variables passing statistics and passing the first year differed as a function of background variables. If so, the relevant background variables were included in regression analysis as a control.

Gender To examine the relation between gender and passing the statistics course and the relation between gender and passing the first year, chi-squared tests of independence were performed. There was no significant relation between gender and passing statistics (χ^2 (1, N=1,027)=.20 p=.65) (47.3 % of the males and 49.4 % of the females passed the statistics exam) or between gender and passing the first year (χ^2 (1, N=1,029)=2.30, p=.13) (34.1 % of the males and 41 % of the females passed the first year). Gender was not included in the regression analysis.

Educational background: high school diploma A chi-squared test indicated a significant relation between SE diploma and passing statistics (χ^2 (7, N=1008)=131.53, $p<.01$) and between SE diploma and passing the first year (χ^2 (7, N=1010)=130.47, $p<.01$). To determine the differences, post hoc Tukey tests were used in ANOVA analysis. Pass-fail distributions as a function of SE diploma are displayed in Fig. 2.

Students with a general educational background (GSE1, GSE2, and GSE3) passed the statistics course and the first year more often than students with technical or arts SE. Within the pool of students with a general educational background, students coming from programs with a higher focus on exact sciences and classical languages (GSE1 and GSE2) scored higher than students coming from programs that focus on social sciences, modern languages, and economics (GSE4). The latter did not significantly differ from students with a vocational secondary background. They did differ from students with a technical and arts background on passing the statistics course and from students with a TSE on passing the first year.

None of the students with a background of VSE (N=6) passed (the statistics course). Due to this very small cell frequency, the analyses showed no significant differences in passing (statistics) from any other group of students. Students with a non-Flemish diploma (N=16) only differed significantly from students with a GSE1 and GSE2 background on both outcomes. High school diploma was considered a relevant variable, but small cell counts obliged us to aggregate data in four categories: a first category consisting of students with a GSE1, GSE2, or GSE3 diploma; a second group of students having a GSE4 diploma; and students with ASE, VSE, and TSE backgrounds were aggregated in group 3 since these students all come from SE programs that do not specifically prepare for higher education studies. Students with a non-Flemish diploma were in group 4. This group was discarded in regression analyses because of the low cell frequencies and because this group was probably very heterogeneous in content. An overview of aggregated group outcomes is presented in Table 2.



CATEGORIZATION OF SECONDARY EDUCATIONAL BACKGROUND (Rombaut, 2006)

GSE1 (8.1% of sample): General Secondary Education with emphasis on Greek-Latin, Greek-Sciences, Greek -Mathematics, Latin-Mathematics
GSE2 (13.1% of sample): General Secondary Education with emphasis on Latin-Sciences, Mathematics-Sciences
GSE3 (18% of sample): General Secondary Education with emphasis on Latin-Modern languages, Modern languages-Mathematics, Economics-Mathematics
GSE4 (51.3% of sample): General Secondary Education with emphasis on Economics-Modern languages,Modern languages-Sciences, Sports-Sciences, Social Sciences
TSE (4.2% of sample): Technical Secondary Education
ASE (1.4% of sample): Artistic Secondary Education
VSE (0.6% of sample): Vocational Secondary Education
Non-Flemish SE (1.5% of sample)

Fig 2 Distribution of secondary education diploma and passed-failed categories of the statistics course (*top*) and the first year (*bottom*)

Table 2 Differences in passing (statistics course) between SE diploma categories

a. Differences in passing statistics course between SE diploma categories				
	GSE1, GSE2, GSE3	GSE4	TSE, VSE, ASE	Non-Flemish
% Passing statistics per SE category	66.2 % a	41 % b	10 % c	25 % b, c
% Failing statistics per SE category	33.8 % a	59 % b	90 % c	75 % b, c
N	405	530	60	16
b. Differences in passing the first year between SE diploma categories				
	GSE 1, 2, 3	GSE 4	TSE, VSE, ASE	Non-Flemish
% Passing per SE category	57 % d	31.9 % e	4.8 % f	12.5 % e, f
% Failing per SE category	43 % d	68.1 % e	95.2 % f	87.5 % e, f
N	405	527	62	16

Each letter denotes a subset of SE categories whose column proportions do not differ significantly from each other at the .05 level

Educational background: hours of mathematics instruction in SE Independent samples *t* tests confirmed the positive effect of a stronger focus on mathematics instruction in SE on passing the statistics exam and passing the first year of university (see Fig. 3).

Students passing the statistics exam had more hours of mathematics in their educational background (M=4.04, SD=1.75) than those who did not pass (M=3.11, SD=1.28) ($t(874)=-8.92$), $p<.01$). Students passing the first year successfully also had significantly more mathematics in their SE programs (M=4.08, SD=1.66) than those who did not pass the first year (M=3.22, SD=1.47) ($t(876)=-7.98$, $p<.01$).

Hours of mathematics instruction during educational training was hence included in the regression analyses.

Predicting achievement from mathematics score

The next step was determining to what extent our mathematics test could predict achievement. To this end, sequential logistic regressions were conducted using SPSS 19.0.

Predicting statistics achievement from mathematics score To predict statistics achievement, we ran sequential logistic regressions with passing statistics as dependent variable.

Independent variables entered the regression in two blocks. First, educational background was entered consisting of "SE diploma" category and "hours of mathematics in SE." Secondly, "mathematics test score" was entered.

The chi-squared test statistic of the model with educational background variables alone was statistically significant, χ^2 (3, N=863)=114.89, $p<.01$. After addition of the mathematics test score, χ^2 (4, N=863)=175.80, $p<.01$. The total number of correct classifications was 68.5 %, which was substantially higher than classification based on the proportion of students failing the statistics course in the sample (48.8 %). Comparison of log-likelihood ratios for models with and without the mathematics test score showed significant improvement with the addition of mathematics test score, χ^2 (1,863)=60.91, $p<.01$. Hours of mathematics in SE and mathematics test score did not interact.

A model in which only the mathematics test score was included predicted 65.3 % of the cases successfully with Nagelkerke R^2=.21.

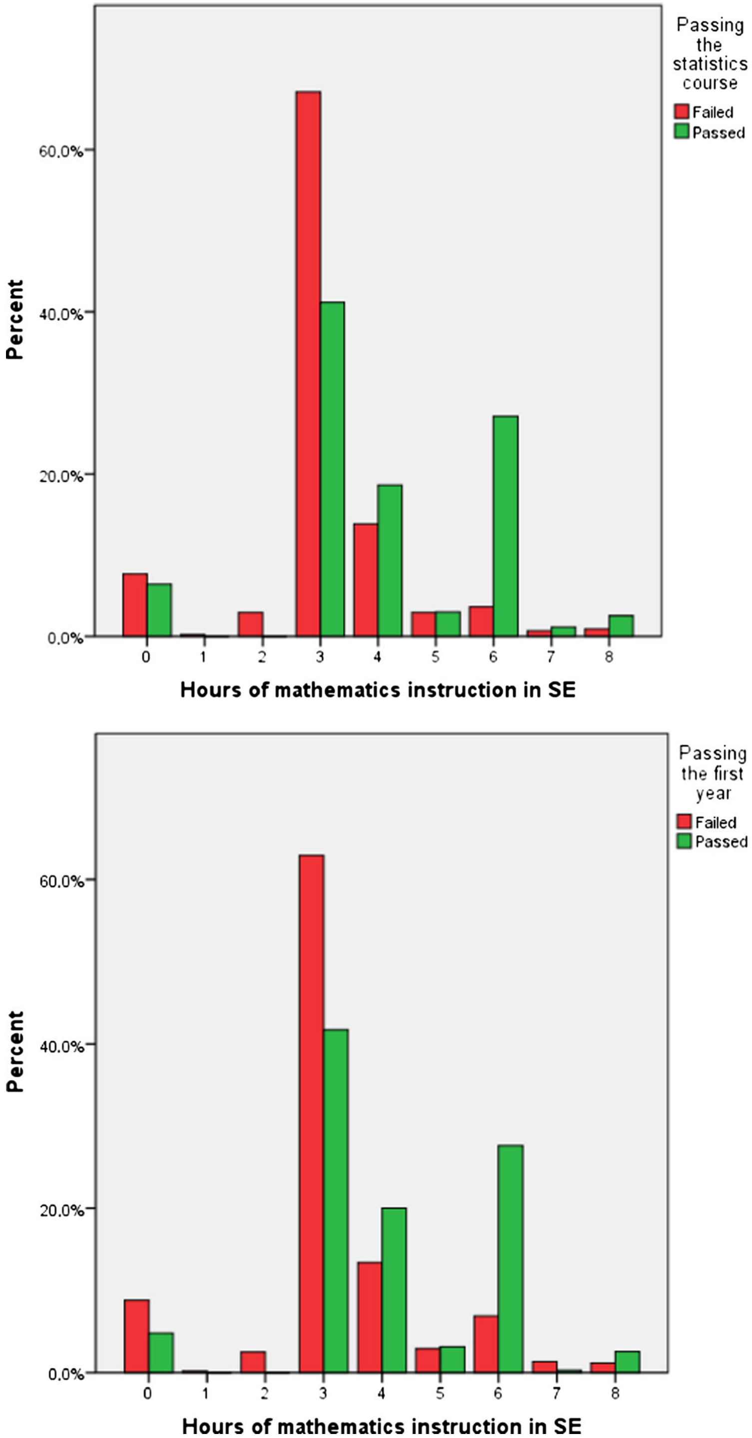


Fig 3 Hours of mathematics instruction in secondary education and pass-fail distributions of the statistics course (*top*) and pass-fail distributions of the first year (*bottom*)

The model with all three predictors was best in terms of percentage of correct classifications. Table 3 presents an overview of parameter estimates of this model.

The score on our mathematics test significantly contributed to the explanation of the variance in passing the statistics exam. The test score alone added 8 %, over and above SE background. SE category and the mathematics test score together explained 25 % of the variance in passing the statistics exam.

Predicting non-mathematical course results and first year achievement from mathematics score Sequential logistic regressions were repeated with passing psychology and passing sociology as dependent variables. The mathematics test score added 3.6 % of the explained variance of passing psychology on top of the 10.2 % explained by educational background factors, χ^2 (4, N=864)=80.43, p<.01. For passing sociology, the mathematics test score added a significant 2.9 % of the explained variance over and above the 8.4 % explained by background variables, χ^2 (4, N=855)=72.89, p<.01. These results showed that the mathematics test score aids the prediction of success in non-mathematical courses as well.

To predict general achievement, passing the first year was used as dependent variable. A model in which only the mathematics test score was included predicted 67.1 % of the cases successfully with Nagelkerke R^2=.15. Analysis showed that a model with educational background variables alone improved prediction of passing the first year, χ^2 (3, N=865)=109.25, p<.01. After addition of the mathematics test score, χ^2 (4, N=865)=140.08, p<.01, Nagelkerke R^2=.20. The percentage of correct classifications was 67.5 %, which was substantially higher than classification based on the proportion of students failing the first year in the sample (40 %). Comparison of the models proved a significant contribution of the mathematics test score to the prediction of passing the first year successfully, χ^2 (1, 865)=30.83, p<.01. This was the best model in terms of percentage correct classifications. The mathematics test score added 4.2 % to the explained variance in passing the first year, over and above SE background variables. Table 4 presents an overview of parameter estimates of this model.

The score on the mathematics test significantly contributed to the explanation of the variance in passing the first year successfully. The mathematics test proved to have predictive validity over and above SE background. Twenty percent of the

Table 3 Logistic regression parameter estimates and model evaluation—predicting passing statistics course

Secondary education diploma	B	S.E.	Odds ratio
GSE1, GSE2, GSE3 (reference cat.)			
GSE4	−.42***	.17	.66
TSE, ASE, VSE	−1.89***	.58	.152
Mathematics test score	.20***	.03	1.22
Hours of mathematics instruction SE	.22***	.06	1.24
Model evaluation			
Chi-square	175.80***		
Nagelkerke R^2	.25		
Percentage of correct classifications	68.5		

***p<0.001

Table 4 Logistic regression parameter estimates and model evaluation—predicting passing first year successfully

Secondary education diploma	B	S.E.	Odds ratio
GSE1, GSE2, GSE3 (reference cat.)			
GSE4	−.53**	.17	.59
TSE, ASE, VSE	−3.20**	1.03	.04
Mathematics test score	.14***	.03	1.15
Hours of mathematics instruction SE	.18***	.06	1.20
Model evaluation			
Chi-square	140.08***		
Nagelkerke R^2	.20		
Percentage of correct classifications	67.5		

**$p<0.01$; ***$p<0.001$

variance in passing the first year successfully was explained by SE background and the mathematics test score, with the mathematics test score adding 4.2 % of the explained variance in passing the first year. The model accurately predicted 67.5 % of the cases.

Discussion

Statistics and methodology courses are often seen as a threat to the attainment of a degree (Onwuegbuzie 1995), especially in social science programs. Success rates in the current study confirm this perception. Of the students who passed the statistics course, 79.2 % passed the first year successfully, and none of the students failing the statistics course passed their first year.

Despite the relatively low performance on statistics examinations, only a few studies have yet investigated predictors of success in such courses (Budé et al. 2007; Galli et al. 2011; Kennett et al. 2009; Macher et al. 2011; Onwuegbuzie 2003b). Basic mathematical skills have been found a relevant variable in the prediction of statistics achievement, a variable that may be more important than previously recognized (Johnson and Kuennen 2006).

If basic mathematical skills contribute to the variance in statistics achievement and there is a high correlation between statistics achievement and general achievement, the question rises whether a basic mathematics test can contribute to the prediction of general academic achievement. In this study, we answered this question positively. To our knowledge, this study was the first to address the relation between basic mathematical skills needed to succeed in introductory statistics courses and overall academic success.

We constructed a test that is short and easy to administer, assessing extremely basic mathematical skills considered vital to pass introductory statistics courses. Results showed that the mathematics test score significantly contributed to the prediction of passing the statistics course, adding 8 % of the explained variance over and above SE diploma and hours of mathematics instruction in SE. Moreover, the mathematics test score also explained variance in the non-mathematical courses of introductory psychology and sociology. This supported us in the proposition that basic mathematics skills contribute to the prediction of overall academic achievement. The basic mathematical test score did indeed explain, together with SE diploma, 20 % of the variance in passing the first year successfully or not. The mathematics test score alone accounted for 4.2 % of the explained variance. The model correctly classified 67.5 % of the cases.

This number is not sufficient to identify all at-risk students and to properly inform students on expected capacities in higher education, but it certainly helps in alerting some individuals with potential deficits in the required numerical mastery. It is noteworthy that a test of very basic mathematical problems significantly contributes to the prediction of overall academic success. Moreover, the test is very brief, consisting of only 20 items, which makes it quick and easy to administer.

These results have several practical implications. The results confirm the implicit feeling of teaching staff and student counselors that knowledge of basic math operations is vital to academic success in the first year at university and that there is a group of students that lack this basic knowledge. The basic mathematical skills test allows identification of the students that have a high probability of failing the statistics course and, as a consequence, the first year of the psychology or educational science program. After assessment, enrolled students that lack these basic mathematical skills can be encouraged to take up remedial courses in mathematics. Moreover, the test allows pupils, SE teachers, and student counselors to evaluate objectively whether or not someone has acquired the necessary mathematics skills to pass an introductory statistics course. As such, the test is valuable not only for students that are already enrolled in the programs, but also for pupils that are in the process of choosing a field of study in higher education. The test aids potential students in evaluating whether they master the required skills to pass the introductory statistics course and their first year of higher education. This is priceless information in a system that has open access to higher education, that has no standardized tests, and where not all pupils have mathematics in their SE curriculum.

This study also shed light on the relation between SE background and academic achievement in higher education social science programs. We found that students with more hours of mathematics instruction in SE had significant better results in higher education. Regardless of the hours of mathematics instruction, the specific SE program also showed related to both statistics achievement and overall first year academic achievement. Overall, students from GSE programs passed significantly more often than did students from technical, arts, or VSE programs. This is not surprising, since the latter programs focus more on direct entrance into the labor market whereas only the GSE programs specifically prepare for continuation into higher education. Nevertheless, even within GSE programs, we found significant differences in success rates. Students coming from programs with a higher focus on exact sciences and classical languages performed better than students coming from programs that focus on social sciences, modern languages, and economics. Although these results are in line with previous data (Declercq and Verboven 2010; Rombaut 2006), they are somewhat surprising. One would expect that a background in economics, which relies on mathematical principles, would provide a sufficient basis for statistical courses in higher education. Even more deterrent is the fact that students coming from a SE program that focuses on social sciences have relatively low success rates in tertiary education programs in that same field of study. One possible explanation could be that students from "more difficult" SE programs have a heavier workload which encourages the development of specific study skills that allow them to cope more effectively with higher education demands. A second reason could be that SE social sciences programs might focus less on the methodological and statistical components that are crucial in the higher education curricula of these majors. As such, wrong ideas of what these programs entail could be fostered. The explanation that is most often proclaimed is the selection effect (Declercq and Verboven 2010), whereby "weaker" students in the course of their SE gradually choose programs that are viewed as "easier," such as the social sciences program. Nevertheless, these underlying reasons have as yet not been studied and open up an interesting area of research.

There are a few limitations to our study. First, mathematics test scores were negatively skewed. This was an inevitable consequence of the test goal, because the purpose was to detect insufficiencies in basic knowledge. Therefore, skewness in test score distribution does indicate a ceiling effect. This ceiling effect may limit the size of the observed correlations in the current study, because the discriminatory power of the test is aimed at the lower end of the scale. The present correlations may hence reflect a lower bound estimate of true predictive validity of post-SE numerical tests. By adding extra items with higher difficulty, the test might be able to discriminate more at the high end. Second, we only addressed the ability to predict first year grades from the mathematics test. We cannot yet determine to what extent the test has predictive value for long-term results such as persistence and timely graduation. A more longitudinal approach is thus recommended and is on our agenda. Next, it would be interesting to examine whether the relation between the mathematics test and passing is found in other fields of study, for example, in programs where statistical courses are not compulsory. Finally, only basic mathematical skills and SE background were taken into account. There are many additional individual differences that have been studied in relation to academic achievement, such as intelligence (e.g., Busato et al. 2000; Kuncel et al. 2004), personality traits (e.g., De Fruyt and Mervielde 1996; Lounsbury et al. 2003; O'Connor and Paunonen 2007), and motivational factors (Budé et al. 2007; Steinmayr and Spinath 2009). Likewise, psychosocial and study skills factors have been observed to significantly contribute to the prediction of academic achievement (Robbins et al. 2004). Despite the overwhelming amount of literature on predicting academic achievement, the combination of cognitive and non-cognitive factors is less often studied.

The mathematics test is only a beginning in the search for a model that takes into account most relevant factors in the prediction of academic success. It is our intention to add different variables to the model to increase predictive power. More background variables, other skills and personality, and motivational and self-efficacy factors will be added in future work. By combining cognitive and non-cognitive factors, we hope to develop a model that provides increased predictive validity and is thus valuable to educators, student counselors, and students. Our general aim is to help identifying at-risk students and to help future students in evaluating their cognitive and non-cognitive abilities in order to choose a major that best suits their potential and background.

Appendix

Appendix Twenty-item mathematics test

Item	Question	Answer format
1	You write a number with the digit 1, the digit 2, and the digit 3. All of these digits are used precisely one time. How many different numbers can you write?	Open answer
2	If a runner runs on average 1 km in 5 min, how many has he run after 2 h?	Open answer
3	Complete: If $x/y=0.25$, then $y/x=$	Open answer
4	Calculate: $8-0.8*5=$	Open answer
5	Calculate: A book has a 40 % discount and costs €18. What was the price of the book before the discount was subtracted?	Open answer
6	Calculate: $4*0.8=$	Open answer
7	Complete: If $x-y=0.5$, then $y-$x=	Open answer
8	Is this expression correct? $(a+b)+(-c-d)=(a-c)-(b-d)$	a. Yes
		b. No
9	Calculate: $3/5*(-2)+1/5=$	Open answer
10	In a group of 400 people, there are 270 men and 130 women. The proportion of low-skilled women is 0.4. How many women in this group are low-skilled?	Open answer
11	Calculate: $(-1)-(-6)$	Open answer
12	What is smaller than 1?	a. $1/2+5/9$
		b. $7/8+1/4$
		c. $2/3+4/12$
		d. $2/5+1/4$
		e. None of the above
13	Calculate: The square root of 0.01	Open answer
14	What is correct?	a. $0.023>0.05$
		b. $0.05>0.023$
15	$f(x)$ is the amount of gas in my car in function of the distance x (in km, since the last time I filled up the car). $f(x)=50-0.05x$. How many kilometers can I drive before the tank is empty?	Open answer
16	Find x. $2x^2+4=3x^2-5x=$	Open answer
17	Calculate: 2/16	Open answer in percentage
18	A car uses 6 L of gas in 100 km. How much gas does it use in 250 km?	Open answer
19	Calculate: $2/3*3/2=$	Open answer
20	Complete: 24=75 % of	a. 0.32
		b. 18
		c. 32
		d. 36
		e. None of the above

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Axiomatic foundations of Multicriteria decision aiding. Voting theory. Measurement theory. Decision under uncertainty. Bibliometrics.

Most relevant publications in the field of Psychology of Education:

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Current themes of research:

Mediation analysis and causality. Analysis of fMRI data.

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Current themes of research:

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Current themes of research:

Applied data analysis. Structural equation modeling

Most relevant publications in the field of Psychology of Education:

Rosseel, Y. (2012). Lavaan: an R package for structural equation modeling. *Journal of Statistical Software, 48*(2), 1–36.

Welvaert, M., Tabelow, K., Seurinck, R., & Rosseel, Y. (2013). Adaptive smoothing as inference strategy. *Neuroinformatics, 11*(4), 435–445.