At-risk at the gate: Prediction of study success of first-year science and engineering students in an open-admission university in Flanders

Any incremental validity of study strategies?

Maarten Pinxten [1]*, Carolien Van Soom [2], Christine Peeters [3], Tinne De Laet [4], and Greet Langie [1]

[1] *Leuven Engineering and Science Education Center, Faculty of Engineering Technology, KU Leuven, Leuven, Belgium*

[2] *Leuven Engineering and Science Education Center, Faculty of Science, KU Leuven, Leuven, Belgium*

[3] *Leuven Engineering and Science Education Center, Faculty of Bioscience Engineering, KU Leuven, Leuven, Belgium*

[4] *Leuven Engineering and Science Education Center, Faculty of Engineering Science, KU Leuven, Leuven, Belgium*

Requests for reprints should be addressed to Dr. Maarten Pinxten, Willem de Croylaan 56, Box 2203, 3001 Leuven, Belgium (e-mail: maarten.pinxten@kuleuven.be).

This work was supported by the Erasmus+ Strategic Partnership programme under Grant 2014-1-BE02- KA200-000462

At-risk at the gate: Prediction of study success of first-year Science and Engineering students in an open-admission university in Flanders

Any incremental validity of study strategies?

Abstract

Against the background of the increasing need for skilled scientists and engineers, the heterogeneous inflow of incoming students in science and engineering programmes is particularly challenging in universities with an open-admission system. The prime objective of the present study is to determine the main academic and non-academic determinants of study success in a STEM study programme in the largest university of Flanders (Belgium). The Learning and Study Strategies Inventory (LASSI), supplemented with additional background questions, was completed by 1,521 first-year science and engineering students at the start of the academic year. To evaluate the incremental value of a particular predictor in explaining first-year GPA, a series of nested regression models were evaluated. Math level and math/science GPA in secondary school were strongly related to first-year GPA. Analysis of the LASSI questionnaire showed that students' motivation/persistence, concentration, and time management skills at the start significantly influenced student achievement at the end of the first year, although the incremental value over prior achievement was small. Altogether, our results show that incoming students' ability to regulate their study efforts has beneficial consequences in terms of achievement. Additionally, a negative recommendation by the secondary school teacher board was a clear indicator to identify at-risk students. In open-admission universities wherein new students cannot be formally denied access based on weak prior mathematics and science achievement, a focus on effort-related self-regulatory skills training (e.g., time management sessions) offers valuable opportunities for remedial interventions.

Keywords: at-risk students; STEM; study skills; achievement

Introduction

Over the past decades, research interest in factors associated with attrition in Science, Technology, Engineering, and Mathematics (STEM) study programmes has grown exponentially. Declining interests in science and engineering among high school students combined with increased needs by the labour market of skilled scientists and engineers are often put forward as the main drivers underlying this increased research interest (French, Immekus, & Oakes 2005). This imbalance is an important challenge for 21st century higher education institutions (HEIs). As pointed out by Ehrenberg (2010), increasing the proportion of students who persist in a STEM study programme by even a small percentage "…*has the potential to be a cost efficient way to substantially contribute to the supply of STEM graduates and workforce*" (p. 889).

Determinants of Study Success in the STEM Field: Empirical Evidence

Prior Achievement and Course-Taking in Secondary School

Prior achievement of students in secondary school, either expressed as their grade point average (GPA) or school leaving matriculation test scores (e.g., Scholastic Aptitude Test – SAT; American College Testing – ACT; or A-level score), are the most consistent predictors of student performance in a STEM study programme in higher education (Pinxten et al. 2015; Richardson, Abraham, & Bond 2012). A high math GPA in secondary school and high mathematics scores on a school leaving matriculation exams are positively related to student performance in the first year of a STEM programme, both in terms of GPA and persistence throughout the programme (e.g., Ackerman et al. 2013; De Winter and Dodou 2011; French, Immekus, & Oakes 2005; Huy, Robbins, & Westrick 2014; Leuwerke et al. 2004; Somers 1996; Van Soom and Donche 2014; Veenstra, Dey, & Herrin 2008). Despite some common variance, secondary school math grades provide significant incremental validity over standardized test scores and vice versa in predicting student achievement. When combined in a regression model, both types of prior achievement indicators show a significant positive relation with later STEM study success (e.g., Ackerman et al. 2013; French, Immekus, & Oakes, 2005; Veenstra, Dey, & Herrin 2008; Zhang et al. 2004). For example, French and colleagues (2005) observed that math GPA and math SAT score together explained 18% of the variance in first-year engineering students' grades at university. Given the importance of standardized test scores for university admission, most international tests should be considered high-stakes tests.

Rigorous mathematics and science course-taking in secondary school is strongly related to students' persistence in STEM programmes (Ashford et al., 2016). Students who took advanced STEM courses in secondary school, generally show higher levels of achievement and persistence throughout the programme (e.g., Ackerman et al. 2013; Eagan et al. 2010; Elliot et al. 1996; Tyson 2011).

Given the overwhelming evidence for the pivotal role of students' prior math/science achievement and course-taking in explaining first-year achievement in a STEM programme, we will predominantly focus on studies that examine the incremental value of other predictors after controlling for prior math and science achievement in secondary school.

Teacher Judgements of Academic Achievement

Subjective teacher judgements of (future) student achievement also have considerable impact on students' educational trajectories (Südkamp et al., 2014) and students' performance (Pinxten et al., 2010). Meta-analysis in this field show that teachers judgements show a high degree of accuracy when compared with standardized test results (Südkamp et al., 2012). Secondary school teachers spend considerable time with their students and are in unique position to evaluate students' academic potential. For example, in the field of medicine, Yates and James (2007) showed that a negative comment in the head teacher's report was related with lower grades and more failed clinical examinations. The latter finding shows that secondary school teachers hold important information regarding the future study success at university. However, scientific research in this field is scarce.

Self-Efficacy Beliefs and Self-Regulatory Skills

Although not specifically oriented towards the STEM domain, two meta-analyses thoroughly investigated the strength of the relation between a number of psychological factors and student performance at university. Richardson, Abraham, and Bond (2012) discriminate between five conceptually distinct types of variables: Personality traits (1), motivational factors (2), self-regulatory learning strategies (3), approaches to learning (4), and contextual factors (5). The authors showed that conscientiousness (i.e., self-disciplined and achievement oriented), effort regulation (i.e., persistence and effort when faced with challenging academic situations), and academic self-efficacy beliefs (i.e., favourable perceptions of oneself's academic capabilities), were all significantly related to students' GPA at university, collectively accounting for 20% of the explained variance (even after controlling for secondary school GPA and SAT scores). Analogously, Robbins et al. (2004) observed a strong relation between academic self-efficacy beliefs, achievement motivation and university GPA (also see Jones et al., 2010). Even after taking into account students' prior achievement (high school GPA and SAT scores), both psychosocial constructs positively affected first-year GPA.

In the STEM field, Ackerman et al. (2013) found that math and science self-concept and a mastery orientation (i.e., high levels of metacognitive self-regulation, effort regulation, and time management) were both positively related to persistence in STEM study programme, even after controlling for secondary school math GPA and SAT scores. However, from a gender perspective, it seems that the positive effect of academic self-concept on achievement is somewhat more pronounced for male than for female students (Van Soom and Donche 2014). Tynjälä et al. (2005) observed that a high degree of self-regulation combined with a deep learning strategy was positively related to study success in engineering programmes.

Study Skills and Strategies

In their meta-analysis, Credé and Kuncel (2008) found that study motivation and study skills (e.g., time management, critical thinking) had a significant incremental validity in predicting freshman GPA over and above both admission test scores and secondary school grades. This finding demonstrates the importance of study behaviour that students exhibit in secondary school before coming to university. However, this empirical evidence of the role of study strategies is predominantly investigated in the field of humanities. Research on the predictive validity of this type of covariates is largely lacking in the STEM field. The present study aims to fill this gap.

University Admission in Flanders

A substantial number of studies investigated factors related to attrition rates in the STEM field (e.g., Ackerman et al. 2013; Bernold, Spurlin, & Anson 2007; Burtner 2005; De Winter and Dodou 2011; French, Immekus, & Oaks 2005; Perez, Cromley, & Kaplan 2014; Seymour and Hewitt 1997). However, there are large differences in the type of institutions typically involved in these studies. Most studies are conducted in highly selective Anglo-Saxon institutions (e.g., Ackerman et al. 2013; Burtner 2005; French, Immekus, & Oakes 2005; Perez, Cromley, & Kaplan 2014). In these institutions, first-year students passed a rigorous selection procedure based on academic (e.g., prior scores on national standardized matriculation exams) and non-academic (e.g., personal statements or selection interviews) criteria.

Unlike most other countries, the transition to higher education in Flanders, the Dutch-speaking region of Belgium, does not involve any formal selection methods or entrance criteria (except for the study programmes Medicine, Dentistry and Arts Education - for more information, See Pinxten et al. 2014): (1) no national school-leaving examinations are organized at the end of secondary education, and (2) no entrance examinations are organized by HEIs. As a consequence, there is a large degree of heterogeneity of incoming students in terms of prior knowledge, attitudes, and skills. This issue is particularly challenging for STEM programmes given that a substantial number of students register with a weak to very weak math and/or science background. In the following paragraphs, we will discuss two elements that play a central role in the transition to higher education in Flanders: diagnostic tests and advice of the teacher board in secondary school.

Diagnostic tests

To address the heterogeneous inflow of incoming students, STEM faculties at Flemish universities expressed an increasing need for a diagnostic test that assesses candidate students' ability to solve math and science problems before enrolment. Therefore, since 2013, diagnostics tests are organised at most Flemish universities at the end of the secondary school (Vanderoost et al. 2014, 2015).

The diagnostic tests are constructed following strict procedures. In the initial phase, a first draft is composed using a table of specification that includes both the topics and difficulty of the items. Subsequently, this first draft is individually assessed by first-year lecturers and tutors. Next, a meeting is organized with all assessors to reach a consensus on the proposed test items. In the final phase, the diagnostic test is offered to independent reviewers (e.g., math secondary school teachers) who comment on the test items and focus on assessing item difficulty. Thereafter, the final version is constructed.

In the last week of the academic year, graduated secondary school students come to university campus where they are given four hours to complete the test. Participation to the diagnostic test is voluntary and the result is non-binding: if a student does not pass the test, s/he can still enrol for that programme. In contrast with most international standardized tests, the diagnostic test is a low-stakes test with little consequences for admissions (see Cole and Osterlind 2008). As such, the voluntary diagnostic test primarily aims (1) to assist students in making a well-balanced decision by offering a comparative frame of reference and (2) to stimulate less successful students to participate in remediation initiatives before the start of the academic year (e.g., math summer course) or to reconsider their choice.

The diagnostic test shows close similarities with placement tests administered in other open-admission universities: rather than serving an admission purpose, both tests are used to assess students' math readiness and to guide decisions about initial mathematics course enrolment (Fitchett et al. 2011; Norman et al. 2011). As such, both types of tests assist students in bridging the gap between secondary and higher education. Also, in both cases, students can ignore the recommendations provided by the test results. However, an important difference between the Flemish diagnostic test on the one hand and placement (and related diagnostic tests; e.g., Robinson & Croft 2003) tests on the other is the timing of administration: Almost all placement test are administered after enrolment whereas the diagnostic test in Flanders is administered before university registration. Research on similar diagnostic test administered prior to university entry is scarce and the present study aims to fill this gap.

Advice Teacher Board Secondary School

In almost all Flemish secondary schools, Grade 12 teachers are intensively involved in the decision-making process of their students. In the last term, students are asked to provide the teachers with their preferred study programme in the first year of higher education. After consulting all teachers in a teacher board meeting, students are individually informed if the teacher board expects they can be successful in this respective study programme and subsequently, if they agree with the student's choice. The recommendations are non-binding: even if teachers issue a negative recommendation to a particular student for choosing a particular study programme at university, this student can still register for this programme. Additionally, teacher recommendations are strictly kept at the secondary school level and are not available for HEI's. To date, there is no empirical research on the accuracy of these teacher recommendations and whether they are related to students' achievement in the first year at university. In line with Yates and James (2007), one of the objectives of the present study is to evaluate the accuracy of these teacher recommendations in an open-admission system.

Objectives and Research Questions

Although a dichotomous risk-classification is ubiquitous in the literature on engineering attrition (Litzler & Young 2012), the degree to which students are at-risk should be considered as a continuum. Rather than classifying students in different risk categories, the prime objective of the current study is to examine which variables are most useful to identify at-risk students in a leading science and engineering education institution in Flanders without formal entry requirements. More specifically, this study will address the following research questions:

1. Is math course-taking in secondary school related to student achievement at the end of the first year?

2. Is there any incremental value of math and science GPA in explaining student achievement at the end of the first year over math course-taking?
3. Is there incremental value of a knowledge-based diagnostic test in explaining student performance at the end of the first year over math course-taking and math and science GPA?
4. Is there incremental value in including study strategies in the identification of at-risk students in a STEM study programme over more traditional performance indicators (e.g., prior achievement) ? Are there differential effects between study programmes?
5. What is the impact of a negative teacher recommendations on student achievement at the end of the first year? What is the incremental value of teacher recommendations in predicting first-year GPA over more conventional predictors (e.g., math course-taking and math/science GPA)?

Method

Participants

An extensive questionnaire was presented to 1,643 new first-year students during the first two weeks of the academic year 2015-2016. Altogether, 1,521 students (M_{age} =17.70 years) in the following STEM study programmes filled in the questionnaire (response rate 92.6%): Bioscience Engineering (N=256 – 48% female), Engineering Science (N=429 – 16% female), Engineering Science – Architecture (N=73 – 53% female), Engineering Technology (N=459 – 12% female), Sciences – MIP (Mathematics, Informatics & Physics – N=120 – 24% female) and Sciences – CBBGG (Chemistry, Biology, Biochemistry, Geography & Geology - N=175 – 49% female). Except for the Science faculty (electronic data collection), all questionnaires were administered in the class-room using paper and pencil.

Measures

Math course-taking. In Flemish secondary education, three intermediate levels of mathematics can be taken: Low (less than six weekly hours of mathematics), medium (six or seven hours), and advanced (eight hours). The mathematics curriculum corresponding to each level differs substantially. In our sample, 55% of the students enter a STEM programme with a medium level of mathematics and 11% starts a STEM study programme with a low level of mathematics. As shown in Figure 1a, the profile of the incoming student population differs substantially between study programmes with respect to the mathematics level. For example, the proportion of students with a low level math background is very low (3%) in Engineering Science whereas this proportion is substantially higher (34%) in CBBGG (Chemistry, Biology, Biochemistry, Geography, and Geology) programmes of the Science faculty.

[INSERT FIGURE 1 HERE]

Math and Science GPA. In most Flemish secondary schools, students receive grades expressed as a percentage for each subject separately. In this study, grades were coded into five categories (below 60%, 60-70%, 70-80%, 80-90%, and above 90%) for the following subjects: Mathematics, Physics, and Chemistry. As mentioned above, no official school leaving exams are organised. Alternatively, math and science teachers in each secondary school compose the final test in their respective subject. In contrast with national matriculation exam scores, student grades are school-dependent and cannot be perfectly placed on a common metric.

Diagnostic test. The diagnostic test was administered 3 months before the start of the academic year (before admission). Participation rates of the voluntary diagnostic test differ substantially between the different faculties: Sciences – CBBGG (20%), Sciences – MIP (40%), Engineering Technology (16%), Bioscience Engineering (24%), and Engineering Science

(88%). At the latter faculty, students earn 1 ECTS credit (out of the 60 regular ECTS credits) if they pass the diagnostic test, resulting in substantially higher numbers of participating students. Given this high participation rate, we will focus on Engineering Science students to evaluate the incremental value of the score on the diagnostic test in predicting first-year achievement (Research Question 3). At this faculty, the diagnostic test focuses on mathematics (30 items) and is graded on a 0 to 20 point scale (M=11.99 ; SD=3.11). If students obtain 10/20, students passed the test (pass rate: 86%).

Learning and study strategies. In order to assess incoming students' learning and study strategies, the Learning and Study Strategies Inventory (LASSI, Weinstein and Palmer 2002) was administered. The LASSI is a 77-item questionnaire that consists of 10 scales: Attitude, Motivation/persistence, Time management, Anxiety, Concentration, Information processing, Selecting main ideas, Study aids, Self-testing, and Test strategies. As such, the LASSI instrument integrates motivational, effort-related and cognitive components. Using factor analysis, Cano (2006) identified three underlying latent constructs: Goal strategies (anxiety, test strategies & selecting main ideas), Comprehension monitoring strategies (information processing, study aids & self-testing), and Affective strategies (Time management, concentration, motivation & attitude). It should be noted that the latter construct is labelled 'Effort-related strategies' by Olaussen and Braten (1998) and closely reflects effort-related self-regulation strategies (i.e., keeping focus when studying, planning/organisation skills, persisting when confronted with challenging tasks).

All items are rated on a 5-point Likert type scale ("*Not at all typical of me*" - … - "*Very much typical of me*"). For each scale, sum scores were calculated and cut-off values were determined to discriminate five norm groups: 'Very weak', 'Weak', 'Average', 'Good', and 'Very good' (Olivier et al. 2015). A comprehensive description of each scale and proportion distribution is provided in Table 1.

[INSERT TABLE 1 HERE]

Advice teacher board. Given the lack of a formal framework, the advice of the teacher board was assessed using a single item constructed by the authors for this purpose. On a 4-point Likert-type scale, students were asked to indicate which type of recommendation they received from the teacher board agreed regarding the chosen study programme ("*Full positive advice*" – "*Partially positive advice*" – "*Negative advice*" – "*No advice*").

Student achievement: Outcome criteria

In order to evaluate the most consistent predictors of first-year students' achievement, following outcome measures were included in this study. First, the proportion of credits obtained is considered. Expressed as a percentage, this is the number of ECTS credits passed at the end of the first year divided by the total number of ECTS credits taken in the beginning of the year (M=55.75; SD=31.92). A full annual study programme contains 60 ECTS credit points. Students who do not obtain 30% of their credits at the end of the first year, are no longer allowed to proceed in this study programme (in our sample, 24.4% of the students did not obtain 30% of their credits or dropped out). Second, we also considered students' weighted GPA (expressed as a percentage) at the end of the first year as a second outcome measure (M=48.89%; SD=17.22). Since the proportion of obtained credits are not distributed normally, students' weighted GPA is used as dependent variable in all regression analyses (research questions 2-5). For students who dropped out before participating in any of the exams, no weighted GPA was calculated (5.2% of sample).

Analysis

To evaluate statistical differences in the proportion of credits obtained between students with different math levels (Research Question 1), and teacher recommendations (Research Question 5), ANOVA-tests were performed.

To gauge the predictive validity of the predictor variables, a series of nested regression models were tested (for the total sample, Model 1-5; see Table 2). A stepwise approach was administered wherein independent variables were added in accordance with the empirical evidence observed in the literature. Given the larger explanatory power of academic measures, these independent variables were tested first (e.g., math level, math/physics/chemistry GPA). Non-academic measures were added in a second stage. To evaluate the incremental value of one model over another, increases in the adjusted R^2 (proportion of variance explained) were tested on statistical significance using F-tests. In order to address the third research question, we ran all models separately for the Engineering Science students (Model 6-11). The most relevant comparison is between Model 7c (without diagnostic test) and Model 8 (with diagnostic test).

[INSERT TABLE 2 HERE]

Results

Math Course-taking Secondary School

Significant differences in the proportion of credits obtained after the first year were observed for students with different math levels in secondary school, $F(2, 1435) = 26.67$, $p < .001$. Students with a low math level background on average obtained 40% of the credits after the first year (Figure 1b). For students with a medium and high math level background, this percentage increased to 56% and 61% respectively. As mentioned above, there are substantial differences between study programmes regarding the inflow of students with a different math background (Figure 1a). However, in almost all study programmes, significant differences were observed for the different levels of math background: Bio-science engineering, $F(2, 258) = 3.17$, $p = .04$; Engineering Science, $F(2, 387) = 9.10$, $p < .001$; Engineering Science – Architect, $F(2, 64) = 2.84$, $p = .07$; Engineering Technology, $F(2, 444) = 7.95$, $p < .001$; Sciences – MIP, $F(2, 105) = 3.55$, $p = .03$; and Sciences – CBBGG, $F(2, 162) = 3.59$, $p = .03$.

Math and Science GPA Secondary School

When combined together, prior math GPA and math level (Model 2a) explain 17% of the variance in students' weighted GPA at the end of the first year (Table 2). As shown in Figure 2, students with both a low math level background and poor prior math grades, obtained significantly less credits at the end of the first year. For example, 61% of the students with a low mathematics background and a math GPA ranging between 60 and 70% (N=31) did not obtain 30% of their credits after the first year in a science or engineering programme. It should be noted that an advanced math level could be considered a necessary but not sufficient condition for future study success: 43% of the students with an advanced level mathematics background but a math GPA below 60% (N=20) obtain less than 30% of their credits after the first year. This proportion is about four times lower for similar students with a math GPA above 80%.

The inclusion of prior Physics GPA (Model 2b) and Chemistry GPA (Model 2c) results in an R^2 of 19% and 22% respectively. In sum, students' secondary school background (math course-taking and math/science GPA) accounts for almost a quarter of the variance explained in student achievement at the end of the first year.

[INSERT FIGURE 2 HERE]

Incremental Value of Math Diagnostic Test (Engineering Science)

A simple regression model with only secondary school math GPA explains 22% of the variance in weighted GPA scores at the end of the first year. A similar model with only the math diagnostic test score as a predictor results in the same proportion of explained variance. Thus, when considered separately, both measures have similar predictive power in explaining first-year performance. However, when both variables are combined, the proportion of variance explained increases to 34%.

Even after taking into account secondary school math level and math/science GPA, the math diagnostic test still has significant incremental predictive value: the inclusion of the math diagnostic test score (Model 8) results in an R^2 increase of 6% compared to model 7c (see Table 2).

Learning and Study Strategies

As shown in Table 3, four out of ten LASSI scales show a significant positive correlation of more than .20 with students' weighted GPA at the end of the first year: Motivation/persistence ($r=.26$), Time management ($r=.24$), Concentration ($r=.22$), and Test strategies ($r=.21$). As such, the effort-related self-regulation skills predominantly contribute to student success at the end of the first year. A stepwise regression model with all ten scales yielded following result: Only three scales (Motivation/persistence, Test strategies, and Time

Management) significantly contributed to the prediction of weighted GPA at the end of the first year, F (3, 1380) = 46.15, $p < .001$, resulting in an R^2 of 9.1%.

[INSERT TABLE 3 HERE]

To evaluate the incremental predictive validity of the LASSI scales over prior achievement, Motivation/persistence (Model 3) and Time management (Model 4) were added to a model with secondary school GPAs and math level included (Model 2c), resulting in an additional 2% and 3% of the variance explained, respectively (Table 2). Corresponding changes in F-value indicate that these improvements of the model are statistically significant. The inclusion of the Test Strategies scale yielded no significant improvement in variance explained so this model was discarded.

Thus, incoming students' motivation and time management skills have a small but significant contribution to their grades at the end of the first year. For example, students with average or above average time management skills have a significantly higher weighted GPA at the end of the first year in comparison with students with very poor time management skills, even after taking into account prior achievement (Table 4).

[INSERT TABLE 4 HERE]

Differences between study programmes. In order to further explore differences between the study programmes, the final model 5 was considered separately for each study programme. Illustratively, we will focus on the science programmes Chemistry, Biology, Biochemistry, Geology and Geography (CBBGG). For these programmes, secondary school GPAs did not significantly contribute to the prediction of the weighted GPA (Table 4). In these programmes, especially motivation/persistence and time management skills showed a significant relation with the weighted GPA after the first year. For example, students with a very high level of motivation attained a GPA that is 13.09% higher compared to students with a very low motivation level. For the other study programmes, the regression coefficients were similar to the general model 5, indicating only small differences between study programmes.

Advice Secondary School Teacher Board

As shown in Table 5, 51% of the students reported a full positive advice of the secondary school teacher board. This means that for about half of the students in our sample, the teachers in secondary school were fully confident that each of those students has the required knowledge and skills to be successful in their preferred study programme. However, 8% of the students reported a negative recommendation from the secondary school teacher board. ANOVA analysis shows that there are significant differences in proportion of credits obtained between students with a different advice, $F(3, 1435) = 83.34$, $p < .001$. Students with a full positive advice on average obtained 67% of the credits at the end of the first year (only 13% of these students obtained less than 30% of the credits). By contrast, students with a negative advice on average obtained only 31% of the credits (59% of these students obtained less than 30% of the credits).

[INSERT TABLE 5 HERE]

As shown in Table 2, the inclusion of the advice of the teacher board (Model 5) results in an R^2 increase of 4% after controlling for math level, math and science subjects GPAs, motivation/persistence and time management. The corresponding change in F-value indicates that the inclusion of teacher recommendations has significant incremental value in predicting first-year students' GPA, even after controlling for all other covariates.

This finding seems to hold especially for the CBBGG study programmes. As shown in Table 4, students who received a negative advice (N=15) on average attained a weighted GPA that is 19.53% lower compared to students with a full positive advice (N=76), all other predictor variables held constant. Altogether, these results show that the advice given by secondary school teachers is a powerful tool in predicting the odds on success in the first year in a STEM study programme in an educational context without formal entry requirements.

Discussion

The early identification of students at-risk for underperformance is a glaring issue for universities with an open-admissions culture. In order to give secondary school graduates a realistic prospect of their future study success, such a culture requires a detailed and accurate information flow directed towards a heterogeneous population in terms of prior knowledge and academic skills. In this context, a thorough exploration of the academic and non-academic determinants of study success in the STEM field was the primary objective of the present study.

Consistent with previous studies, secondary school math level and prior math and science GPAs were significant predictors of GPA after the first year, accounting for almost a quarter of the variance explained. Additionally, a negative recommendation from the teacher board in secondary school was a strong indicator for first-year at-risk status: students with a negative advice obtained significantly less credits after the first year compared to students with a full positive advice. Due to their regular close contact with students, secondary school teachers seem to be in a unique position to evaluate the odds of future study success of their students. As such, these results demonstrate that teacher recommendations could be a valuable addition to existing placement tests in open-admission universities.

In line with results of the meta-analysis of Robbins et al. (2004), this study shows that motivation/persistence accounts only for an additional 1%-2% of variance in students weighted GPA after controlling for prior achievement and math level in secondary school. This result, however, cannot be generalized over study programmes. For students in a Chemistry, Biology, Biochemistry, Geography, or Geology study programme, a higher motivation/persistence was more strongly related to higher GPA scores at the end of the first year. A tentative explanation for the different results pattern at the CBBGG programmes, is likely to be found in the heterogeneity of incoming students in terms of secondary school programmes: there is a wide variety in educational background of these students. This heterogeneity undermines a straightforward interpretation of obtained math and science grades and this most likely results in the non-significant effects of these covariates in our regression analysis. Hence, this calls for great caution when using prior achievement as an indicator for the identification of at-risk students in these programmes. Altogether, these findings shows that even within the STEM field, there is no one-size-fits-all risk identification mechanism that generalizes over all study programmes.

In line with meta-analytical results of Credé and Kuncel (2008), moderate correlations between effort-related self-regulation strategies (e.g., Time-management, Concentration, Motivation, classification by Olaussen and Braten 1998) and first-year GPA were observed. However, after the inclusion of prior achievement indicators in our model (math level, math/science GPAs, and math diagnostic test score), the incremental predictive validity of these constructs was rather small, suggesting little added value for the identification of at-risk students.

Importantly, because of their self-reported nature, non-academic measures are not ideal to use in formal admission procedures (Ackerman et al. 2013; Ellingson & McFarland 2011). However, the non-ability measures explored in this study are a good start to provide students with feedback, before or after registration, on which aspects of their study behaviour they need to improve in order to increase academic achievement.

The Benefits of a Voluntary Diagnostic Test in an Open-Admission University

Although inherent to the Flemish open-admission system, the lack of a common metric to evaluate (1) students' prior achievement in the field of mathematics, physics, and chemistry and (2) the recommendations of the teacher board is a substantial drawback. However, not controlling for these prior achievement measures would likely result in inflated estimates of learning and study strategies parameters. The results of this study show that a pre-enrolment low-stakes diagnostic test has significant incremental value over students' self-reported grades and that both types of information combined offer a more accurate estimate of students' future achievement at university. However, as outlined by Cole and Osterlind (2008), low-stakes test with little consequences tend to lower both students' effort levels and achievement. The latter issue is particularly relevant in faculties where nothing can be gained by passing the test (only at the Faculty of Engineering Science, one ECTS credit is awarded upon successful completion).

In countries with a long history of standardized admission exams (SAEs), for example the US, the use of these types of tests has been sometimes criticized (e.g., Zwick 2004). One of the opponents' main argument against SAE's is the enormous weight of those tests on students' educational future (e.g., Ricci 2006). However, given its non-obligatory (i.e., students can voluntarily participate) and non-binding (i.e., students can access university even if they fail the test) nature, the diagnostic tests in Flanders do not have the weight of the SAE's in most Anglo-Saxon countries.

An open-admission university has the responsibility towards graduating secondary school students to inform them on their individual math and science abilities. This process starts with carefully phrased feedback of test results and a continuous critical evaluation of the content and difficulty level of the diagnostic tests. It was demonstrated that these diagnostic tests have the potential to be a beneficial instrument for both student guidance counsellors and graduating students. On the one hand, student guidance counsellors are offered an extra tool to identify at-risk students at the start of the academic year. Graduating high school students, on the other, are given the opportunity to compare their performance in the math and science domain with a wider population of incoming students. Additionally, in case of a low test result, remedial interventions (e.g., summer courses in math and/or chemistry) are offered in order to fill knowledge gaps before the start of the academic year.

Limitations and Directions for Future Research

The prime interest of the present study was the identification of the main determinants of study success in the first-year of a STEM study programme. However, the models presented here do not lend themselves for individual prediction of study success in counselling practice. The present study provides a first impetus on how different sets of variables could be combined (e.g., poor math GPA and time management skills) but more research is needed to determine which particular interactions yield the highest risk indication.

In this context, it should be noted that there are more variables at stake that directly or indirectly influence student achievement at the end of the first year. In this study, we primarily focused on malleable student characteristics at the start of the academic year. However, other research has shown that gender (e.g., French et al. 2005; Jones et al., 2010), socio-economic status (e.g., Richardson et al. 2012), and personality traits (e.g., Komarraju, Karau, & Schmeck

2009) also significantly contribute to the prediction of study success at university. Additionally, the relations observed in the present study should not be interpreted in isolation of events that take place throughout the academic year (i.e., social and academic integration, Pinxten et al. 2015; Tinto 1987).

In contrast with effort-related self-regulatory skills, little to no effect of goal strategies (e.g., anxiety or selecting main ideas) or comprehension monitoring strategies (e.g., information processing or self-testing) on student achievement was observed in this study. An important consideration when investigating the effects of the both types of strategies on achievement in the STEM domain is the adequacy of existing instruments to measure these constructs. For example, as pointed out by Greene (2015), the differential effects of shallow and deep learning strategies on academic achievement are less clear in the STEM domain. As such, an important direction for future research is to critically evaluate the items of contemporary instruments that aim to measure these goal and comprehension monitoring strategies.

Except for the diagnostic test scores and first-year students' GPA (official university records), all data in the present study were collected through self-reported measures. Given that there is no structural information flow between secondary and higher education, educational background information (i.e., secondary school grades, math level, teacher recommendations etc.) is not available to HEI's neither prior nor after registration. As stipulated by Gonyea (2005), especially in an admission procedure, students make themselves look more desirable. It is reasonable to assume that this type of bias also applies to the current study (i.e., self-reported secondary GPAs might be slightly inflated). However, as pointed out by the author, the accuracy of the self-reported background information tends to be high when the information requested is known to the respondent. This is clearly the case for, for example, math educational background (which is well-known to all students). In order to minimize the bias in measuring students' learning strategies, the LASSI questionnaire was selected. This established instrument has a long validation history wherein validity and reliability are thoroughly investigated. However, it should be noted that the use of these type of instruments in a high-stakes selection context might compromise their validity (due to socially desirable answer patterns).

Implications for Practice

An important consideration/challenge for each study that empirically examines at-risk students is the transfer to educational practice. Complex statistical models with large number of variables do not offer student guidance counsellors in the field the necessary tools to provide meaningful feedback to students. For example, competence and self-efficacy beliefs (i.e., self-perceptions of one's abilities in a particular domain) have been shown to have a strong relation with first-year student performance (e.g., Richardson, Abraham, & Bond 2012; Robbins et al. 2004). In their study, van Dinther et al. (2011) summarized different intervention methods to increase students' self-efficacy beliefs. However, as noted by the authors, repeated negative mastery experiences might undermine efforts to improve self-efficacy beliefs. Analogously, Ackerman et al. (2012) noted that trait-like constructs (e.g., personality), albeit they hold some predictive power, "*… are relatively stable and not generally amenable for modification*" (p. 925). In this respect, a focus on, for example, time management skills has greater potential. Zimmerman (2002) identifies managing one's time use efficiently as one of the key processes of the self-regulation of learning. In training students to use their time more effectively, a central role is reserved for metacognition (i.e., an awareness of and knowledge about one's own thinking/learning behaviour). In this respect, self-observation (e.g., asking students to record their time use to make them more aware of time spend on studying) can generate valuable insights. It should be noted that the impact of such training interventions is highly dependent on the type of study skill training (See Hattie, Biggs, & Purdue 1996).

Conclusion

A low math level background, poor math and science GPAs, a negative advice from secondary school teachers, and, to a lesser extent, poor effort-related self-regulatory skills are among the prime indicators for underperformance in the first year of a science and engineering programme. From a student guidance perspective, the latter finding is of paramount importance in an open-admissions system given that students cannot be formally excluded from registration on the basis of weak prior achievement. A focus on a malleable skill set provides valuable training opportunities for low-performing students who decide to enrol in a science and engineering programme. Finally, the high predictive value of secondary school teachers' recommendations calls for a closer collaboration between HEI's and secondary schools in decision-making processes in an open-admission system.

References

Ackerman, P.L., Kanfer, R., & Beier, M.E. (2013). Trait complex, cognitive ability, and domain knowledge predictors of baccalaureate success, STEM persistence, and gender differences, *Journal of Educational Psychology*, *105*, 911-927. doi: 10.1037/a0032338

Ashford, S. N., Lanehart, R. E., Kersaint, G. K., Lee, R. S., & Kromrey, J. D. (2016). STEM Pathways: Examining Persistence in Rigorous Math and Science Course Taking. *Journal of Science Education and Technology*, *25*, 961-975. doi: 10.1007/s10956-016-9654-0

Bernold, L., Spurlin, J.E., & Anson, C.M. (2007). Understanding our students: A longitudinal study of success and failure in engineering with implications for increased retention, *Journal of Engineering Education*, *96*, 263-274. doi: 10.1002/j.2168-9830.2007.tb00935.x

Burtner, J. (2005). The use of discriminant analysis to investigate the influence of non-cognitive factors on engineering school persistence, *Journal of Engineering Education*, *94*, 335-338. doi: 10.1002/j.2168-9830.2005.tb00858.x

Cano, F. (2006). An in-depth analysis of the Learning and Study Strategies Inventory (LASSI). *Educational and Psychological Measurement*, *66*(6), 1023-1038. doi: 10.1177/0013164406288167

Cole, J.S., & Osterlind (2008). Investigating differences between low- and high-stakes test performance on a general education exam. *The Journal of General Education*, *57*, 119-130

Credé, M., & Kuncel, N. R. (2008). Study habits, skills, and attitudes: The third pillar supporting collegiate academic performance, *Perspectives on Psychological Science*, *3*, 425–453. doi: 10.1111/j.1745-6924.2008.00089.x

De Winter, J.C.F., & Dodou, D. (2011). Predicting academic performances in engineering using high school exam scores, *International Journal of Engineering Education, 27,* 1343-1351. doi: 0949-149X

Eagan, K.M., Hurtado, S., & Chang, M.J. (2010). What matters in STEM. Institutional contexts that influence STEM bachelor's degree completion rates, *Annual Meeting of the Association for the Study of Higher Education, Indianapolis.*

Ehrenberg, R. G. (2010). Analyzing the factors that influence persistence rates in STEM field, majors: Introduction to the symposium, *Economics of Education Review, 29,* 888–891. doi:10.1016/j.econedurev.2010.06.012

Ellingson, J. E., & McFarland, L. A. (2011). Understanding faking behavior through the lens of motivation: An application of VIE theory, *Human Performance, 24,* 322–337. doi:10.1080/08959285.2011.597477

Elliott, R., Strenta, A. C., Adair, R., Matier, M., & Scott, J. (1996). The role of ethnicity in choosing and leaving science in highly selective institutions, *Research in Higher Education*, *37*, 681-709. doi: 0361 -0365/96/1 200-0681

Fitchett, S., King, K., & Champion, J. (2011) Outcomes of Mathematics Placement: An Analysis of Advising and Enrollment Data, *PRIMUS, 21*, 577-591. doi: 10.1080/10511970903515323

French, B.F., Immekus, J.C., & Oakes, W.C. (2005). An examination of the indicators of engineering students' success and persistence, *Journal of Engineering Education*, *94*, 419-425. doi: 10.1002/j.2168-9830.2005.tb00869.x

Gonyea, R. M. (2005). Self-reported data in institutional research: Review and recommendations. *New directions for institutional research*, *2005*(127), 73-89. doi: 10.1002/ir.156

Greene, B.A. (2015). Measuring cognitive engagement with self-report scales. Reflections from over 20 years of research, *Educational Psychologist*, *50*, 14-30. doi: 10.1080/00461520.2014.989230

Hattie, J., Biggs, J., & Purdie, N. (1996). Effects of learning skills interventions on student learning: A meta-analysis, *Review of Educational Research*, *66*, 99–136. doi: 10.3102/00346543066002099

Huy, L., Robbins, S.B., & Westrick, P. (2014). Predicting student enrollment and persistence in college STEM fields using an expanded P-E fit framework: A large-scale multilevel study, *Journal of Applied Psychology*, Advanced online publication. doi: 10.1037/a0035998

Jones, B.D., Paretti, M.C., Hein, S.F., & Knott, T.W. (2010). An analysis of motivation constructs with first-year engineering students: Relationships among expectancies, values, achievement, and career plans. *Journal of Engineering Education*, *99*, 319-336. doi: 10.1002/j.2168-9830.2010.tb01066.x

Komarraju, M., Karau, S. J., & Schmeck, R. R. (2009). Role of the Big Five personality traits in predicting college students' academic motivation and achievement. *Learning and Individual Differences*, *19*, 47-52. doi: 10.1016/j.lindif.2008.07.001

Leuwerke, W.C., Robbins, S., Sawyer, R., & Hovland, M. (2004). Predicting engineering major status from mathematics achievement and interest congruence, *Journal of Career Assessment*, *12*, 135-149. doi: 10.1177/1069072703257756

Litzler, E., & Young, J. (2012). Understanding the risk of attrition in undergraduate engineering, *Journal of Engineering Education, 101*, 319-345. doi: 10.1002/j.2168-9830.2012.tb00052.x

Olaussen, B. S., & Braten, I. (1998). Identifying latent variables measured by the Learning and Study Strategies Inventory (LASSI) in Norwegian college students, *Journal of Experimental Education, 67*, 82-96. doi: 10.1080/00220979809598346

Olivier, I., Lacante, M., & Briers, V. (2015). A re-calibration of the LASSI norm scores for a Flemish educational context (Unpublished Master Thesis). Katholieke Universiteit Leuven, Leuven, Belgium.

Norman K.W. , Medhanie, A.G., Harwell, M.R., Anderson, E, & Post, T.R. (2011). High School Mathematics Curricula, University Mathematics Placement Recommendations, and Student University Mathematics Performance, *PRIMUS*, *21*, 434-455. doi: 10.1080/10511970903261902

Pinxten, M., De Fraine, B., Van Damme, J., Van Den Noortgate, W., Boonen, T., & Vanlaar, G. (2014). "*I choose so I am*". A logistic analysis of major selection in university and successful completion of the first year, *Studies in Higher Education*, *40*, 1919-1946. doi: 10.1080/03075079.2014.914904

Pinxten, M., De Fraine, B., Damme, J., & D'haenens, E. (2010). Causal ordering of academic self-concept and achievement: Effects of type of achievement measure. *British Journal of Educational Psychology*, *80*, 689-709. doi: 10.1348/000709910X493071

Pinxten, M., De Laet, T., Van Soom, C., & Langie, G. (2015). Fighting increasing drop-out rates in the STEM field: The European readySTEMgo Project. *Proceedings of the 43rd Annual SEFI Conference. Annual Conference of European Society for Engineering Education (SEFI)*. Orléans, France, 1-3 July 2015, pp. 1-8.

Ricci, C. (2006), *Book review: Rethinking the SAT: The future of standardized testing in university admissions* by R. Zwick, *The Journal of Educational Thought*, 40, 177-180

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of University students' academic performance: A systematic review and meta-analysis, *Psychological Bulletin, 138,* 353-387. doi: 10.1037/a0026838

Robinson, C. L., & Croft, A. C. (2003). Engineering students—diagnostic testing and follow up. *Teaching Mathematics and its Applications*, *22,* 177-181. doi: 10.1093/teamat/22.4.177

Robbins, S. B., Lauver, K., Le, H., Davis, D., Langley, R., & Carlstrom, A. (2004). Do psychosocial and study skill factors predict college outcomes? A meta-analysis, *Psychological Bulletin*, *130,* 261–288. doi: 10.1037/0033-2909.130.2.261

Somers, C.B. (1996). Correlates of engineering freshman academic performance, *European Journal of Engineering Education*, *21*, 317-326. doi: 10.1080/03043799608923417

Südkamp, A., Kaiser, J., & Möller, J. (2012). Accuracy of teachers' judgments of students' academic achievement: A meta-analysis. *Journal of Educational Psychology*, *104*, 743–762. doi:10.1037/a0027627

Südkamp, A., Kaiser, J., & Möller, J. (2014). Teachers' Judgments of Students' Academic Achievement. In S. Krolak-Schwerdt, S. Glock & M. Böhmer (Eds.), *Teachers' Professional Development Assessment, Training, and Learning (pp. 5-25).* Rotterdam, The Netherlands: SensePublishers.

Tinto, V. (1987). *Leaving college*. *Rethinking the causes and cures of student attrition*. London: University of Chicago Press.

Tynjälä, P., Salminen, R.T., Sutela, T., Nuutinen, A., & Pitkänen, S. (2005). Factors related to study success in engineering education, *European Journal of Engineering Education, 30,* 221-231. doi: 10.1080/03043790500087225

van Dinther, M., Dochy, F., & Segers, M. (2011). Factors affecting students' self-efficacy in higher education. *Educational research review, 6,* 95-108. doi: 10.1016/j.edurev.2010.10.003

Vanderoost, J., Callens, R., Vandewalle, J., & De Laet, T. (2014). Engineering positioning test in Flanders: a powerful predictor for study success, *Proceedings of the 42nd Annual Conference of European Society for Engineering Education (SEFI)*. Birmingham, UK, 15 - 19 September 2014, pp. 1-8.

Vanderoost, J., Van Soom, C., Langie, G., Van den Bossche, J., Callens, R., Vandewalle, J., & De Laet, T. (2015). Engineering and science positioning tests in Flanders: powerful predictors for study success? *Proceedings of the 43rd Annual Conference of European Society for Engineering Education (SEFI)*. Orléans, France, 29 June - 2 July 2015, pp. 1-8.

Van Soom, C., & Donche, V. (2014). Profiling first-year students in STEM programs based on autonomous motivation and academic self-concept and relations with academic achievement, *PLOS ONE*, *9*, pp. 1-13. doi:10.1371/journal.pone.0112489

Veenstra, C.P., Dey, E.L., & Herrin, G.D. (2008). Is modeling of freshman engineering success different from modeling non-engineering success? *Journal of Engineering Education, 97*, 467-479. doi: 10.1002/j.2168-9830.2008.tb00993.x

Weinstein, C.E., & Palmer, D.R. (2002). Learning and Study Strategies Inventory 2nd Edition. Clearwater, FL: H&H Publishing Company.

Yates, J., & James, D. (2007). Risk factors for poor performance on the undergraduate medical course: cohort study at Nottingham University. *Medical education*, *41*, 65-73. doi: 10.1111/j.1365-2929.2006.02648.x

Zhang, G., Anderson, T.J., Ohland, M.W., & Thorndyke, B.R. (2004). Identifying factors influencing engineering student graduation: A longitudinal and cross-institutional study, *Journal of Engineering Education, 93,* 313-320. doi: 10.1002/j.2168-9830.2004.tb00820.x

Zimmerman, B.J. (2002). Becoming a Self-Regulated Learner: An Overview, *Theory Into Practice*, *41*, 64-70. doi: 10.1207/s15430421tip4102_2

Zwick, R. (Ed.). (2004). *Rethinking the SAT: The future of standardized testing in university admissions*. London: Routledge Farmer.

Table 1

Description, internal consistency (Cronbach Alpha), and relative proportions of students in the different norm groups of the 10 LASSI scales

	Description	Exemplary item	Cronbach Alpha	% Very weak	% Weak	% Average	% Good	% Very good	% Missing
1. Attitude	The importance of going to university and academic success in a student's life	*"I feel confused and undecided as to what my educational goals should be"*	.64	11%	21%	24%	21%	16%	7%
2 Motivation/Persistence*	Students' diligence, self-discipline, persistence, and willingness to exert the effort necessary to successfully complete academic tasks	*"Even when study materials are dull and interesting, I manage to keep on working until I finish"*	.77	12%	18%	25%	24%	14%	7%
3. Time management	Students' tendency to procrastinate and ability to meet deadlines	*"I only study when there is pressure of a test"*	.76	15%	18%	29%	18%	14%	7%
4. Anxiety	Anxiety levels that keep students from performing at the maximum level	*"Even when I'm well-prepared for a test, I feel anxious"*	.84	5%	7%	24%	22%	34%	7%
5. Concentration	A student's ability to direct and maintain attention on academic tasks	*"I find it hard to pay attention during lectures"*	.84	10%	17%	28%	22%	17%	6%
6. Information Processing	A student's ability to make information meaningful and to store it in their memory in a way to recall it easily in the future	*"I translate what I am studying in my own words"*	.81	8%	17%	22%	25%	21%	7%
7. Selecting main ideas	A student's skill to identify important information for further study from less important information	*"It is hard for me to decide what is important to underline in a text"*	.73	11%	16%	22%	33%	12%	6%
8. Study Aids	A student's ability to use and create techniques for meaningful learning	*"I make drawings or sketches to help me understand what I am studying"*	.73	26%	15%	24%	17%	11%	7%
9. Self-testing	The degree to which students monitor their progress when studying	*"I test myself to be sure I know the material I have been studying"*	.71	11%	18%	26%	24%	14%	7%
10. Test Strategies	A student's techniques for preparing for and taking tests	*"I memorize grammatical and technical terms without understanding them"*	.71	8%	16%	28%	29%	11%	7%

* The motivation scale in the LASSI is more a persistence indicator rather than a motivation variable in the classical Self Determination Theory sense

Table 2

Multiple regression models for the total sample (Models 1-5) and for the Engineering Science study programme (Models 6-11) with first-year weighted GPA (%) as dependent variable

TOTAL SAMPLE (N=1,521) – Model 1-5	**Adjusted R^2**	**Δ Adjusted R^2**	**F change**	**Sig F change**
Model 1 (Math level)	4%			
Model 2a (Math level – Math GPA)	17%	13%**	223.2	<0.001
Model 2b (Math level – Math GPA – Physics GPA)	19%	2%**	40.75	<0.001
Model 2c (Math level – Math GPA – Physics GPA – Chemistry GPA)	22%	3%**	47.99	<0.001
Model 3 (Math level – Math GPA – Physics GPA – Chemistry GPA – Motivation/persistence)	24%	2%**	9.54	<0.001
Model 4 (Math level – Math GPA – Physics GPA – Chemistry GPA – Motivation/persistence – Time management)	25%	1%**	4.70	<0.001
Model 5 (Math level – Math GPA – Physics GPA – Chemistry GPA – Motivation/persistence – Time management – Advice teacher board)	29%	4%**	28.32	<0.001
ENGINEERING SCIENCE (N=429) – Model 6-11				
Model 6 (Math level)	6%			
Model 7a (Math level – Math GPA)	30%	24%**	129.27	<0.001
Model 7b (Math level – Math GPA – Physics GPA)	32%	2%**	13.69	<0.001
Model 7c (Math level – Math GPA – Physics GPA – Chemistry GPA)	36%	4%**	28.57	<0.001
Model 8 (Math level – Math GPA – Physics GPA – Chemistry GPA – Diagnostic test score)	42%	6%**	37.50	<0.001
Model 9 (Math level – Math GPA – Physics GPA – Chemistry GPA – Diagnostic test score – Motivation/Persistence)	42%	0%	.958	0.431
Model 10 (Math level – Math GPA – Physics GPA – Chemistry GPA – Diagnostic test score – Motivation/Persistence – Time management)	44%	2%*	2.60	0.036
Model 11 (Math level – Math GPA – Physics GPA – Chemistry GPA – Diagnostic test score – Time management – Advice teacher board)	45%	1%**	4.06	0.007

Note. The inclusion of more LASSI scales yielded no improvement of the model and all matching regression coefficients were non-significant. Statistical Significant changes in Δ Adjusted R^2 *$p < .05$; ** $p<.01$.

Table 3

Raw Pearson correlations between the ten LASSI scales and weighted Grade Point Average (GPA - %) at the end of the first year (N=1,521)

	1	2	3	4	5	6	7	8	9	10	11
1. Weighted GPA (%)	–										
2. Attitude	.16**	–									
3. Motivation/persistence	.26**	.45**	–								
4. Time management	.24**	.38**	.64**	–							
5. Anxiety	.10**	.25**	-.05	.05	–						
6. Concentration	.22**	.49**	.53**	.61**	.27**	–					
7. Information Processing	.09**	.21**	.20**	.11**	.08**	.14**	–				
8. Selecting Main Ideas	.11**	.36**	.78**	.24**	.42**	.40**	.29**	–			
9. Study Aids	.00	.19**	.33**	.31**	-.19**	.16**	.34**	.10**	–		
10. Self-testing	.09**	.29**	.53**	.45**	-.04	.34**	.45**	.25**	.52**	–	
11. Test Strategies	.21**	.47**	.33**	.33**	.49**	.51**	.18**	.64**	-.01	.17**	–
Mean	48.50	31.46	28.33	24.35	27.28	27.10	28.32	17.92	24.13	25.32	29.56
Standard Deviation	17.40	3.52	4.43	4.79	5.24	4.96	4.39	2.77	4.59	4.15	3.77

** p < .01; * p < 05; Max score on the LASSI scales = 40 (except for Selecting Main ideas Max = 25)

Table 4
Unstandardized (B) and standardized (b) regression coefficients of Model 5 for the total sample (N=1,521) and for the programmes Chemistry, Biology, Biochemistry, Geology and Geography (N=175)

	Total Sample (N=1,521)					**CBBGG (N=175)**				
	Unstandardized		Standardized	Sig.		Unstandardized		Standardized	Sig	
	B	St. E.	b	t	p	B	St. E.	b	t	p
Constant	22.86	2.34		9.76	0.00	26.49	6.93		3.82	0.00
Math_Level_Medium [a]	5.32	1.40	0.15	3.81	0.00	3.44	2.65	0.10	1.30	0.20
Math_Level_Advanced [a]	6.43	1.49	0.18	4.31	0.00	6.31	4.45	0.11	1.42	0.16
Math GPA	2.95	0.47	0.17	6.30	0.00	2.28	1.32	0.12	1.73	0.09
Physics GPA	1.37	0.51	0.08	2.70	0.01	0.16	1.60	0.01	0.10	0.92
Chemistry GPA	2.57	0.48	0.15	5.30	0.00	1.63	1.48	0.09	1.10	0.27
Motivation_Very_good [b]	2.63	1.84	0.05	1.43	0.15	13.09	5.91	0.24	2.21	0.03
Motivation_Good [b]	4.15	1.56	0.11	2.66	0.01	6.97	5.17	0.20	1.35	0.18
Motivation_Average [b]	3.36	1.46	0.09	2.31	0.02	10.51	5.22	0.25	2.01	0.05
Motivation_Weak [b]	1.58	1.47	0.04	1.08	0.28	2.54	5.22	0.06	0.49	0.63
Time_management_Very_good [c]	3.89	1.70	0.08	2.29	0.02	8.01	5.01	0.15	1.60	0.11
Time_management_Good [c]	3.32	1.48	0.08	2.25	0.02	9.07	4.40	0.21	2.06	0.04
Time_management_Average [c]	3.59	1.30	0.10	2.76	0.01	10.04	4.05	0.28	2.48	0.01
Time_management_Weak [c]	– 0.30	1.36	– 0.01	– 0.22	0.83	0.40	4.36	0.01	0.09	0.93
Advice_Teacher_Partially_positive [d]	– 6.32	1.06	– 0.15	– 5.95	0.00	– 6.31	3.19	– 0.15	– 1.98	0.05
Advice_Teacher_No_advice [d]	– 7.68	1.09	– 0.18	– 7.04	0.00	– 6.04	3.22	– 0.14	– 1.87	0.06
Advice_Teacher_Negative [d]	– 11.19	1.66	– 0.17	– 6.75	0.00	– 19.53	4.24	– 0.34	– 4.61	0.00
Adjusted R^2	29%					36%				

Note. [a] Reference category: Math level low; [b] Reference category: Very low motivation; [c] Reference category: Very low time management; [d] Reference category: Full positive advice of teacher board; GPA: Grade Point Average.

Table 5

Mean proportion credits obtained (Study Efficiency, SE) and proportion of students with a SE below 30% in function of the advice given by the teacher board at the end of secondary school

	Descriptives		**Achievement**		
	N	%	Mean SE	St. Dev.	Proportion SE <30%
Full positive advice	776	51%	67%	29%	13%
Partially positive advice	322	21%	46%	29%	34%
No advice received	303	20%	45%	32%	38%
Negative advice	113	8%	31%	28%	59%

Note. Statistical difference were tested using ANOVA. $F(3, 1435) = 83.34$, $p<.001$.

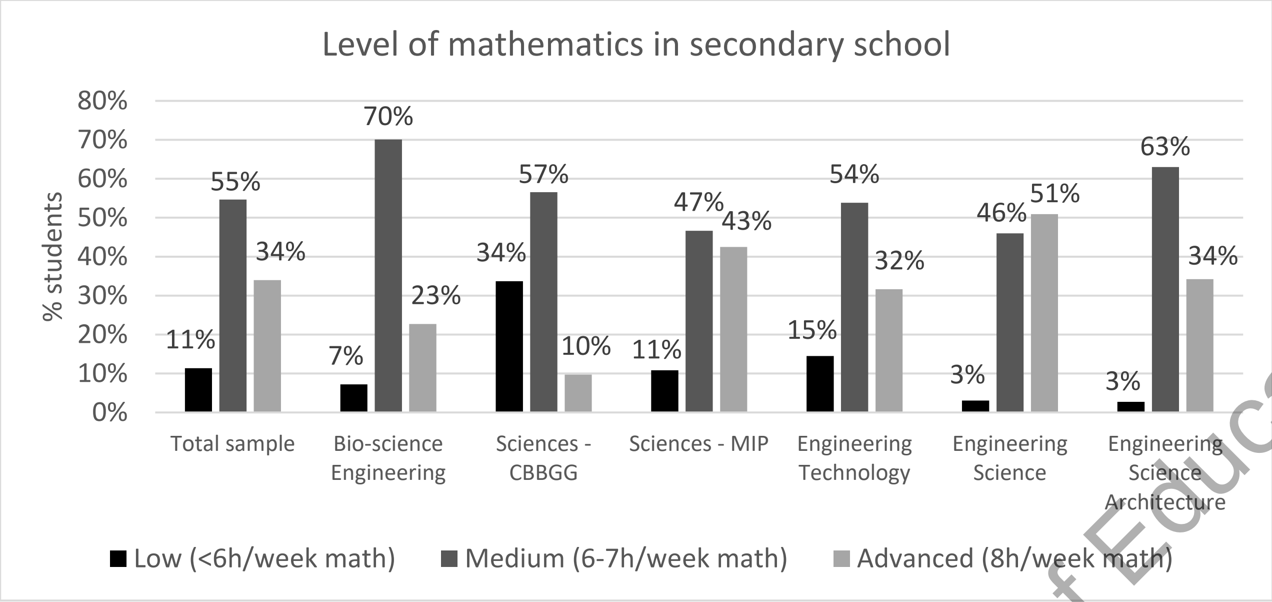

Figure 1a. Math level of incoming students in the different STEM study programmes

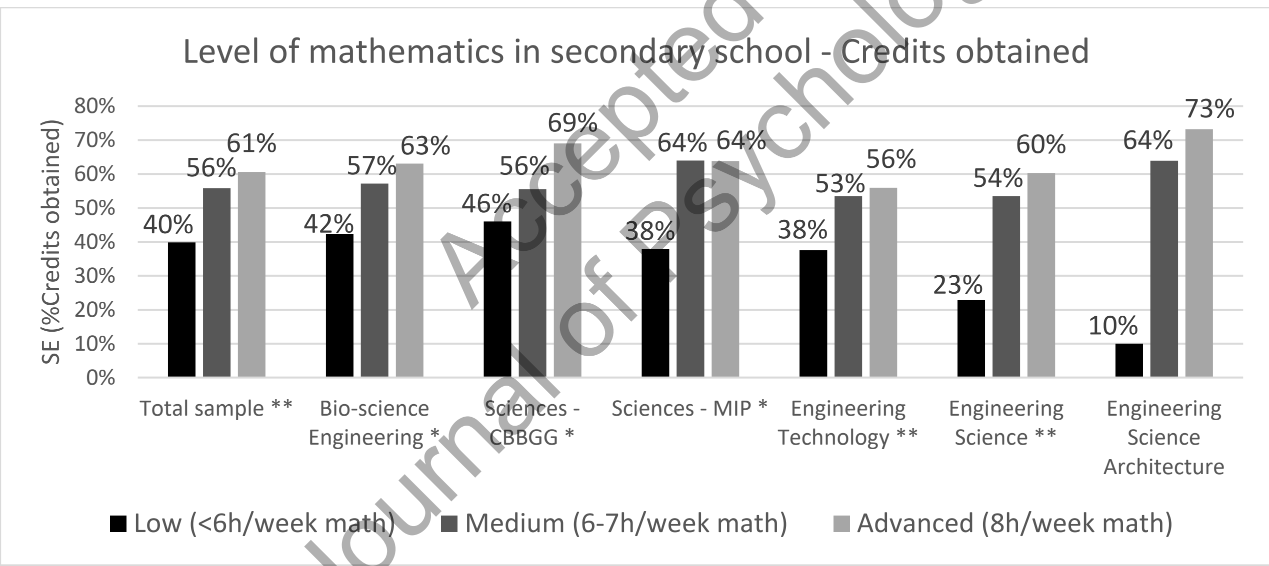

*Figure 1b. Mean % credits obtained at the end of the first year in function of the math level of incoming students in the different STEM study programmes (Differences tested using ANOVA analysis, ** p < .01; * p < .05)*

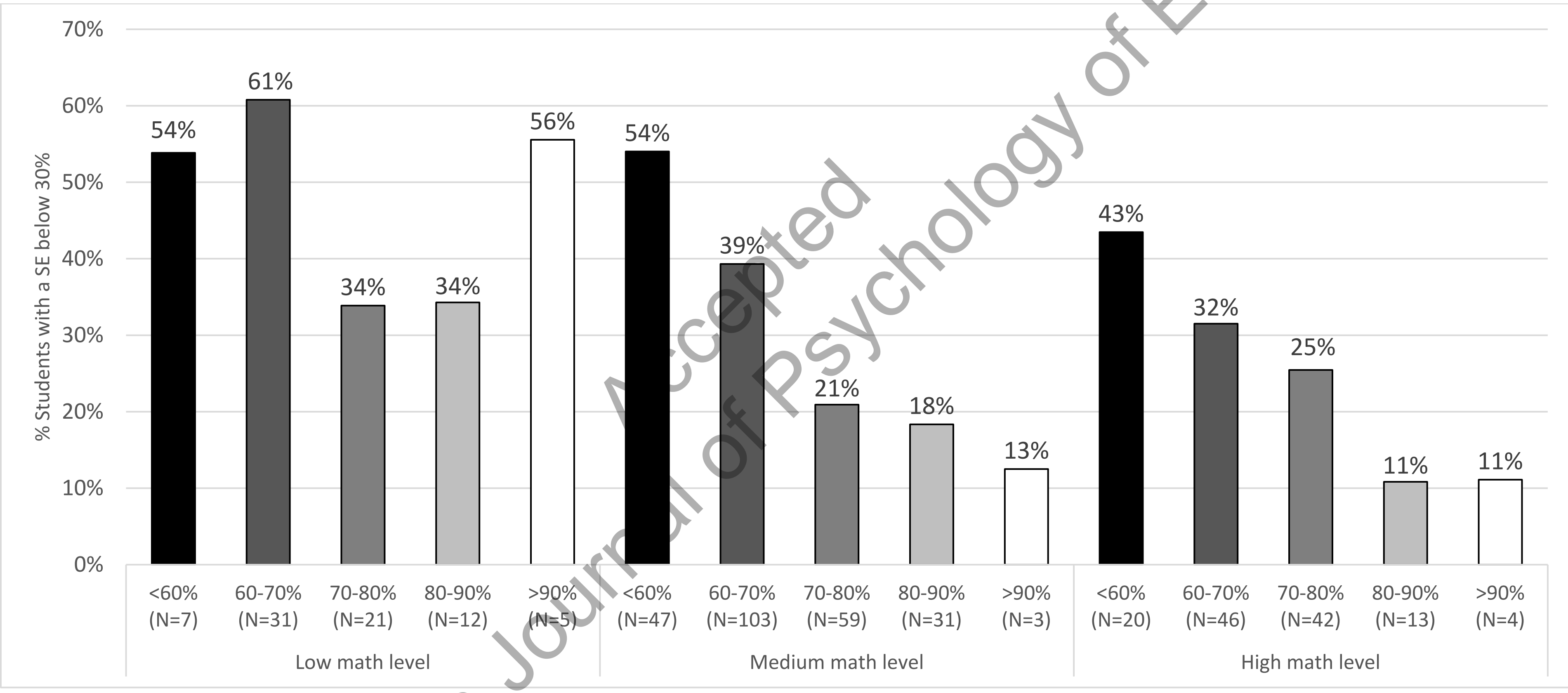

Figure 2. Proportion of students with a Study Efficiency (SE) below 30% or who dropped out as a function of the prior math level and math GPA in secondary school (N=444)