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How Accurately Do Program-Specific Basic Skills Predict Study Success in Open Access Higher Education?

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Abstract

Student fail rates in the first year of open access academic higher education can become dramatically high. The present study in Flanders, Belgium examines how performance on program-specific basic skillsets can identify students at risk at the start of their curriculum in 21 bachelor programs (*N* = 6,624), months before actually failing their exams or dropping out. Results identify up to 58% of the students prone to failure at relatively lower error rates while still adhering to the principles of higher education equity. In practice, institutions and counselors can use the methodology of this study to identify at-risk students and offer them reorientation and remediation trajectories, preventing failure. Future applications towards more restricted or selective international education systems are discussed.

Keywords: *academic achievement; academic achievement prediction; study success; study failure; study orientation*

How Accurately Do Program-Specific Basic Skills Predict Study Success in Open Access Higher Education?

The transfer from high school to academic higher education is a challenging process with a high cost in time and resources all students have to face on their way towards degree attainment (Roser & Ortiz-Ospina, 2013; Tett et al., 2017). This process is especially arduous in open access academic higher education, as students have to navigate two specific assignments in order to attain their degree (Fonteyne, 2017). First, every student must make a life-determining decision in choosing an appropriate study program, as nearly all study programs are open to anyone with a high school degree, without additional requirements. And second, students need to achieve study success in the chosen program in order to stay on track towards degree attainment. These two assignments are not as straightforward as they might seem. As an example, Schelfhout and colleagues (2019) reported that 59% of Flemish students did not pass the first year of open access academic higher education because these students failed one or more courses of their curriculum. Internationally, the Organisation for Economic Co-operation and Development (OECD) reports that 30% (24% for Flanders, Belgium) of all students eventually leaves higher education without a degree (OECD, 2017). As an explanation, the OECD report also points out that not everyone who starts higher education - in open and restricted access - has the same basic skillset to begin with. The OECD (2015) defines basic skills as functional literacy by obtaining level one skills on the PISA scales (Programme for International Student Assessment). As an example, the level one description for mathematics states that students should be able to answer basic questions with direct information in explicit situations. For instance, *the price of a book on a 40% sale is $42; what was the original price of the book?* The prime gateway to acquiring such skills is graduation from secondary education. However, in contrast to education systems with a more restricted setting, the (basic) skillset of students in open access academic higher education is not assessed a priori using test batteries like the SAT (historically called the *Scholastic Aptitude* or *Assessment Test*, see also https://collegereadiness.collegeboard.org/) or the ACT (*American College test*, see also http://www.act.org/). These tests would also not be very appropriate to test the basic skillset of students, as these tests are tailored towards identification and selection of excellent students with the highest potential.

In such a high stakes context of a life determining decision, knowledge about risk of study failure can help identify and council those students who are prone to fail specific programs. By identifying these students early on, counseling advice towards additional tutoring or remediation may improve the student's basic skillset and subsequent chances of success (Fonteyne, Duyck et al., 2017). Alternatively, negative feedback towards the attainability of a student's current program can guide students towards a more appropriate program altogether (Fonteyne et al., 2018). However, whereas a large corpus of research already exists on the predictive value of entry tests focusing on excellence (see Klasik, 2013 for an example), much less research exists on the predictive value of minimal, basic skills towards outcomes in open access higher education.

The present study thus investigates how accurately program-specific basic skill levels can predict study success in open access higher education. In doing so, the present study addresses two issues in literature. First, prediction methodology regarding academic achievement primarily focuses on the explanation of population variance rather than an actual prediction of individual student results (Shmueli, 2010). And second, the extant literature focuses on determining the numbers of failing students at very strict, but fixed error rates (i.e., successful students erroneously predicted as failing) (Fonteyne, Duyck et al., 2017). In the present study, we explore the possibility of allowing more lenient and variable error rates to identify more students at risk of failure in specific programs. This balance between the error rate and numbers of identified failing students will aid counselors and institutions in drawing out an appropriate (i.e., can we justify giving negative advice to students who would still succeed their program?) and feasible (i.e., can my institution handle the extra students for counseling or remediation programs?) counseling policy for specific students and specific programs.

Flemish Open Access Higher Education and Equity

The Bologna Declaration (1999) introduced the European Credit Transfer and Accumulation System to institute a system of comparable, (under)graduate degrees for 29 European countries and to facilitate the access towards the unified European labor market. As requested by the Bologna Declaration (1999), a specific bachelor program in Flemish open access higher education thus consists of 180 ECTS credits. These credits are spread out over three model trajectories of 60 credits each, thus spanning three (consecutive) academic years. Such a model trajectory allocates these credits to a set of program-specific courses analogous to the importance and difficulty of the courses.

For the present study, the open access system in Flanders (Belgium) provides open access to nearly all bachelor programs through low admission costs (i.e., annual enrolment cost of about € 1,000 or $ 1,170) and low prior performance requirements (i.e., a degree that indicates a student has successfully completed secondary education). Students with a low family income have the possibility of applying for additional funding regarding enrolment and the rent of a student room for each of the three years of the model trajectory. This funding can become as high as 100% (i.e., full scholarship) for students with the lowest family incomes (for a full explanation, see https://www.studietoelagen.be/hoger-onderwijs-0).

Such funding policies are crucial as numerous studies show that the social economic status (SES) of students is related to both cognitive ability as well as to performance in higher education (Ceci, 1991). For instance, in 2014 the U.S. Census Bureau reports that students from families with the highest incomes are eight times more likely to obtain a bachelor's degree by age 24 compared to students from families with the lowest incomes (Cahalan et al., 2018). These numbers are exemplary for the effects family SES can have on results in higher education, especially towards equity. Equity in higher education can be described as the right to a qualitative education for every student, with equal chances of success that are not based on variables like family SES, ethnic origin or the education level of one's parents (Heaslip et al., 2017; Jurado de los Santos et al., 2020). Considering the importance of equity in higher education, research has already suggested to methodologically separate the effects of SES and cognitive ability (on study results) as the correlation between both is estimated around $r = .38$ (Levine, 2011; Hanscombe, 2012). Moreover, Van den Broeck (2014) states that across all OECD countries about 15% of the difference in mathematics performance can be attributed to SES differences (OECD, 2013). This result indicates that the vast majority of the differences in cognitive ability and academic achievement is not related to SES. Van den Broeck (2014) therefore suggests that research should not focus on which system of education fails to adhere to equity principles. Instead, research should focus on how we can keep the effects of non-adhering equity variables as small as possible. Research on study success and study orientation should therefore always control for unwanted effects of *non-equity adhering variables*. As such, the present study controls for the effects of family SES on both study results as well as the prediction of study results.

Continuation of the individual funding programs depends on the yearly evaluation of students. A student needs to pass a course with a grade of at least 10 marks out of 20 to obtain the ECTS credits for the course. Each student has to complete their bachelor program in timely fashion as decreed by both the university as well as the (Flemish) government. In case the student makes little progress, the student is officially warned. In such a system, it is of capital importance that each student finds an appropriate program that both fits the student's skills and interests before the student fails too many exams and is denied access to higher education altogether. For students with a low family income, finding an appropriate and attainable program is even more important as the conditions for (the continuation of) funding are more strict compared to the conditions for (the continuation of) access. Orienting students in danger of failing towards remediation (i.e., improving the basic skillset for the specific program) or reorientation (i.e., proposing a different program altogether) can actually support students' access to higher education instead of limiting it. This study orientation is the goal of the SIMON project.

The SIMON Project

The present study focuses on predicting academic achievement by assessing the basic skillset of students towards a specific program. The present study explores the prediction power of these basic skillsets by using data from the SIMON (i.e., Skills and Interest MONitor) project at Ghent University, which aims to dispense program-specific, post-enrolment advice for each student prior to the start of the first bachelor year (Fonteyne, Duyck et al., 2017; Fonteyne, Wille et al., 2017). The advice is based on test results measuring the basic skills and properties to succeed in a specific higher education program. These test results are then validated towards predicting future results using a large historic data base (more than 70,000 entries as of 2021) on test and exam results of former students. If the test results indicate that students have really low chances of success, students can be counseled to upgrade their basic skills or to reorient towards a more suitable program. The ultimate goal of the project is to improve individual student study success. The present study uses a recent prospective data sample (2016-2018) drawn from the SIMON project database to model academic achievement prediction. Important to note, the SIMON advice is not binding, as the final decision towards remediation or reorientation always resides with the student.

The SIMON instrument also adheres to the equity principle and is designed to neutralize the (unwanted) effects of non-equity adhering variables (Fonteyne, 2017). For this equity purpose, SIMON separates cognitive ability from the effect SES can have on schooling prior to higher education by testing basic skills for which little to no formal or specialized schooling is needed (e.g., *the price of a book on a 40% sale is $42; what was the original price of the book?).*

Basic Skills towards Academic Achievement

Modeling the prediction of academic achievement in higher education already has a long standing tradition, taking into account both (non-) cognitive skills and previous achievements (Schneider & Preckel) as well as equity, social background and institutional properties (Tinto, 1993; Tinto, 2012). As OECD reports (2015, 2017) already point out that a difference in basic skillsets could explain why large numbers of students leave higher education without a degree, the present study primarily focuses on basic skills to predict academic achievement. Basic skills are operationalized as predictors. These predictors are typically assessments of cognitive functioning, prior achievements and non-cognitive variables (UNESCO, 2016). First, cognitive predictors include mental abilities that involve reading, writing, numeracy and understanding and executing complex ideas (Green, 2011; Kiely, 2014; Pierre et al., 2014). Next, though closely related to cognitive predictors, prior achievements are often considered a separate category as these achievements show incremental validity above and beyond cognitive predictors (Hodara & Lewis, 2017; Noble & Sawyer, 2002; Poole et al., 2012). Lastly, non-cognitive predictors include thoughts, feelings and behaviors that are socially developed during the lifespan including (but not limited to) personal traits, attitudes and motivations (Borghans et al., 2008; West et al., 2016).

Recently, Schneider and Preckel (2017) reported meta-analytic evidence that success in higher education is mainly predicted by prior achievements (Hodara & Lewis, 2017; Noble & Sawyer, 2002; Pinxten et al., 2017; Poole et al., 2012) and cognitive ability (Rohde & Thompson, 2007; Roth et al., 2015), with (minor) incremental effects from variables like conscientiousness

(Duckworth et al., 2019; Poropat, 2009; Trapmann et al., 2007). In addition to these cognitive variables, Richardson and colleagues (2012) have already added promising meta-analytical results to literature regarding the relation between academic achievement and academic self-efficacy (Bandura, 1993), test anxiety (Credé & Kuncel, 2008) and metacognition (Kitsantas et al., 2008). More recent meta-analytical research has also identified additional non-cognitive variables like vocational interests (Nye et al., 2018) and motivation (Kriegbaum et al., 2018; Ryan & Deci, 2017) as overlooked, yet possible important predictors of academic achievement.

In psychology and educational science, these predictors of academic achievement are usually molded into some form of linear or logistic regression model to evaluate how well the resulting model can explain the population variance in study outcomes like GPA (Sackett et al., 2008). Both the total explained population variance of the model as well as the incremental contributions of the predictors (when controlling for the others) are commonly reported. For instance, Nye and colleagues (2018) recently found that the combination of cognitive ability (e.g., ACT scores), the scores on a situational judgement test, biodata, and interest congruence could explain about 33% of the variance in overall GPA, with interest congruence providing 3% of unique explained population variance above and beyond the other variables. The vast majority of research in psychology and educational science has adopted such an explanative approach.

Interestingly, Shmueli (2010) has correctly pointed out that statistical models with high amounts of explained population variance do not necessarily predict individual results accurately. Using a set of variables to explain population variance in study results and using a set of variables to predict individual study results are the object of two different research aims and traditions (i.e., explanation of variance in a specific population vs. prediction of individual study results in a specific population). When the population variance approach is used correctly, statistical modeling allows to explore the effects and interactions of specific variables on study results.

However, both research traditions in psychological and educational literature are subject to a conflated use of the population variance approach. Indeed, studies are evaluating individual prediction models by considering the explained population variance. Such methodology can cause bias towards the prediction of individual results, which is detrimental to the prime and practical goal of individual orientation advice (see also Lo et al., 2015 for a concrete example on the difference between population explanation and individual prediction). As an analogue example at a more conceptual level, Tinto (2017) made a clear distinction between two related, but different perspectives on study progress: general higher education retention or individual student persistence. While general retention focuses on increasing the proportion of students who obtain their degree, an individual student wants to obtain the desired degree, irrespective of the institution or region in which it is earned. In other words, an explanation of population variance is a valuable tool for investigating general higher education results, but is far less suited to study performance from the perspective of the individual student. For this purpose specifically, the present study primarily investigates how accurately basic skill levels can predict individual study success in open access higher education using appropriate methodology. Additionally, these predictions can also be used at the institutional level to facilitate study (re)orientation for each individual student.

Modeling a Program-Specific Basic Skillset

Before one can use such a set of basic skills to predict study success in a specific program, one has to first extract the set from an available pool of predictors of academic achievement. Fortunately, literature already harbors regression methods to extract optimal sets from a pool of available predictors, with Akaike's Information Criterion (AIC) serving as a prime example (Vrieze, 2012). More specifically, an AIC – stepwise regression procedure extracts a set of predictors towards a criterion by minimizing the chance of information loss, while keeping the number of predictors to a strict minimum. For the present study, the AIC – procedure thus extracts a basic skillset of predictors of academic achievement for each specific program that gives us the best guarantee to distinguish passing and failing students. Also, such a procedure focuses on minimizing prediction errors of full models instead of explaining variance through significant individual predictors (Burnham & Anderson, 2002), which is exactly what Schmueli (2010) advocated. This approach towards full models is also practically warranted as a deficit on one predictor of academic achievement that could jeopardize study success could be compensated by a higher skill level regarding the other predictors of the basic skillset.

Moreover, models in literature that explain variance in academic achievement are almost always run across study programs instead of using a program-specific approach. As an exception, Fonteyne, Duyck and colleagues (2017) did make use of a program-specific approach towards academic achievement as different programs may indeed require different basic skillsets. Results showed that their program-specific approach had a clear edge over a more general approach, with each specific program featuring a unique combination of basic skills towards explaining academic achievement. As such, the study explained up to 29% of the variance in student success across programs. Though the main focus of the study was on explaining population variance, the study also managed to correctly identify an average of 13% (with peaks of 26% for some programs) of the students that were prone to failing their program (true positives), while tolerating a fixed 5% error rate of successful students erroneously considered failing. However, Fonteyne, Duyck and colleagues (2017) did not explore how identification of failing students varied over more lenient error rates, nor did the authors explore how this balance can affect counseling policy. The present study aims to address both issues.

Present Study

The present study investigates how accurately basic skill levels can predict individual study success in open access higher education. Using an AIC – procedure[1] regression method for smaller sample sizes, we have extracted a basic skillset that predicts if students will pass their chosen program. This basic skillset is extracted from a pool of (non-) cognitive abilities that were selected in the literature on academic achievement, and assessed through the Flemish study orientation tool SIMON, prior to university entry (Fonteyne, 2017). The tests in this orientation tool were not designed to be sensitive at high levels of cognitive function, but instead assess basic levels of abilities necessary for university education, in domains like (but not limited to) mathematics, language and conscientiousness. For a more complete overview how such basic skill tests are selected or constructed, we refer to Fonteyne, Duyck and colleagues (2017).

Using the extracted basic skillset for each program, we can predict whether students have sufficient scores on these skills to successfully complete a specific study program. Our main goal is to identify failing students (i.e., true positives), without wrongfully classifying passing students as failing (i.e., false positive error rate). However, we have not fixed the false positive error rate at 5%. Instead, we have explored how many failing students we can correctly identify at different error rates, prior to failing their exams. Considering the premise that not all students start higher education with the same basic skillset (OECD, 2017), considering the nature of the procedure (i.e., extracting a basic skillset from relevant predictors of academic achievement) and considering the nature of our measures (i.e., tailored towards measuring basic levels of abilities needed for study success), we expect that we can create a clear distinction between students who have a fair chance of success and students who have a high chance of failing, based on the levels of acquired basic skills. As such, we should be able to identify the majority of students that lack

[1] The analyses were also replicated with regular AIC and BIC procedures. For each program these analogue procedures rendered an identical set of predictors, showing that even at smaller sample sizes the models rendered are quite robust.

the basic skills to succeed at lower error levels. As a consequence, we expect that the number of additional identified failing students will strongly diminish over increasing error rates until the decrease reaches a turning point after which the number of additional identified failing students is nominal at best. More formally, we hypothesize that the relation between the additional identified failing students and the increase in the error rate behaves according to a limited distribution of exponential decay,

$$f(x) = init + (plateau - init)(\exp(-kx)) \tag{1}$$

in which *x* represents the *error rate* and *f(x)* represents the *increase in identified failing students.* The parameters *init* (for the upper limit), *plateau* (for the lower limit) and *k* (for the steepness of the decay) need to be estimated. The resulting curve of exponential decay is comparable to a so called *forgetting curve* (Murre & Dros, 2015) or a *scree plot* (Saito & Rehmsmeier, 2015).

Method and Materials

Data

The dataset for this study was obtained through the large longitudinal SIMON - project (dataset 2016-2018, see also Fonteyne, Duyck et al., 2017 and Fonteyne, Wille et al., 2017) in Flanders, Belgium (Flanders), featuring a large pool of first-year students (*N* = 6,624, 64% response rate, 60% female). The dataset contains independent samples from eleven faculties and 21 bachelor programs from an open access university (ARWU top 100 of the Shanghai ranking of worldwide universities). The range of program topics is very wide, representing science (i.e., biochemistry), social science (i.e., psychology) and arts and humanities (i.e., history) (Glänzel &

Schubert, 2003)[2]. Each prospective student with a high school degree can freely choose any program at university (with exception of medicine, dentistry and performing arts), without passing a standardized exam or meeting a certain level of high school GPA. All students have to pay a relatively modest yearly tuition fee of about € 1,000 or $ 1,170. Underprivileged students are also entitled to various government scholarships (i.e., 20% of the current sample; scholarship status of two students was unknown). Slightly more than 1% of the students explicitly indicated they had non-native Belgian roots (i.e., parents or grandparents not born in Belgium), while 19% did not disclose this information. About 67% of all students indicated at least one of their parents obtained a bachelor degree, while about 21% of all students indicated none of their parents obtained a bachelor degree. The remaining 12% of the students opted not to disclose this information. In this open academic environment, SIMON aims to provide program-specific advice for each student prior to, and during the first year of an academic bachelor. The advice is based on validated test results, using established predictors of academic achievement as discussed in the introduction. To this extent, the student test results are inserted into a program-specific algorithm, based on a large pool of historical data (more than 70,000 entries as of 2021), containing the test results and exam scores of former students (Fonteyne, 2017). If this comparison indicates that students have really low chances of success, they can be counseled to upgrade their basic skills or reorient towards a more suitable program. The ultimate goal of the project is to improve individual student study success.

The present study uses various test results (collected at the start of the academic year from 2016 until 2018) and subsequent (oral and written) exam and resit results (collected at the end of the first and second semester) from this SIMON database. For the present study, Table 1 shows

[2] The distinction between science, social science and arts and humanities is not always clear-cut. As the focus of the present study was on program-specific prediction, we opted not to explore these differences further.

an overview of these programs, their study success rates and the resulting number of students that are passing or failing their program. Because we are aiming at individual and program-specific prediction, we only incorporated the programs with $n > 100$ students to ensure that models had sufficient power to begin with.

Measures

Dependent Variables

The dependent variables are chosen to disentangle the conflated dichotomy in literature (Schmueli, 2010). Indeed, how well do variables predict academic achievement at the individual level versus how well do variables explain academic achievement in a general population?
The PASS variable is a binary variable (0/1) and indicates whether a student has passed all courses the student enrolled for in a specific program's freshman year. A student that fails to attain all courses will experience a hard time to finish the full program beyond the first year in a timely fashion, as proposed by the model trajectory. For instance, Fonteyne (2017) mentioned that first year results and degree attainment are heavily correlated. Students showing a poor performance in the first year, have little to no chance of obtaining their degree. The present study uses this PASS variable to predict individual study success or failure. In the current sample, 40% of the students successfully completed their first year curriculum, while 60% failed the exam on one or more courses or dropped out prematurely. For the current analyses, we did not differentiate between dropout and failure. Both categories lead to the same result (not passing the first year) and therefore both should be targeted by remediation or reorientation advice as early as possible. For a full discussion on the reliability and validity of study results as dependent measures in a similar open access environment, we refer to Schelfhout and colleagues (2019). However, for the present study, possible bias of these measures due to program-specific or even teacher-specific circumstances is eliminated altogether, as each program is modeled separately

and all students have identical curricula within a specific program (i.e., all students have the same first year courses within one program).

The GPA variable (*M* = 524.13; *SD* = 169.54) is a continuous variable between 0 and 1,000 and provides a global score of students over all courses of their first year curriculum of the specific program. The present study uses this variable to give an indication of the explained population variance of different predictors through correlation analyses.

Prior Achievements

For prior achievements, we incorporated the size of the *high school mathematics package* and *high school GPA*. The high school mathematics package is expressed as the number of weekly hours of mathematics (*M* = 5.00; *SD* = 1.75), and is already known to predict study success in open access environments (Arias & Dehon, 2008; Pinxten et al., 2017).

In practice, the SIMON instrument only measures basic skills and not variables of prior achievement like *high school GPA*, in order to avoid unwanted effects from non-equity adhering variables like SES. As a consequence, the instrument has proven to be SES neutral (Fonteyne, 2017). However, the present study also incorporates self-reported high school GPA ranging from 0 to 100 (*M* = 72.08 ; *SD* = 6.69) as prior achievement is one of the best known predictors of academic achievement (Schneider & Preckel, 2017) and high school graduation is still considered the main gateway towards obtaining functional literacy (OECD, 2015; OECD, 2017). However, following the recommendation made by Van den Broeck (2014), the present study does measure the cost to equity of incorporating high school GPA as a predictor of academic achievement.

Cognitive Predictors

In contrast to classic test batteries (e.g., SAT or ACT) aiming to identify the best students, the cognitive tests in the present study were designed to try and identify those students that were at risk of failing specific programs in higher education due to a lack of basic skills. As a consequence, the tests (mathematics, comprehensive reading and vocabulary) included in the present dataset have a lower difficulty compared to admission tests in more restricted access forms to higher education. For some specific programs like bio-engineering, the data additionally contained a more difficult mathematics test or a more specific chemistry and physics test, developed on-demand from lectors in these programs.

As such, for cognitive ability (with scores ranging from 0 to 20), we tested students on *vocabulary* (M = 17.59, SD = 1.66, Cronbach's α = .79), *comprehensive reading* (M = 14.90, SD = 4.60, Cronbach's α = .65), *mathematics* (M = 16.53, SD = 2.50, Cronbach's α = .83), *chemistry* (M = 15.29, SD = 2.98, Cronbach's α = .98) and *physics* (M = 11.88, SD = 3.53, Cronbach's α = .96).

For vocabulary, we used the lexTALE test (Lemhöfer & Broersma, 2012) in which students had to assess whether the presented stimulus was an existing word or not (60 items). For comprehensive reading, students were asked five questions on a text of medium length about a social psychological experiment. The test had a multiple choice (MC) format with four options. For the mathematics test, students had to fill out 20 questions (MC format with four options and open questions) on elementary mathematics. Items included simple math problems like "A book that is on a 40% discount costs $18. How much did it cost prior to the discount?". For the chemistry test, students had to fill out 20 questions (MC format with four options). Items included elementary questions like "What is the total number of valence electrons of a sulfur atom?". For the physics test, students again had to fill out 20 questions (MC format with four options). Items included elementary questions like "What is Newton's first law?".

Non-Cognitive Predictors

For *autonomous* and *controlled motivation*, we assessed students using the Self-Regulation Questionnaire (Vansteenkiste et al., 2009). Students had to indicate how much they agreed with statements such as “I’m motivated to study this program because I’m supposed to do this” (controlled motivation, eight items) or “I’m motivated to study this program because I want to learn new things” (autonomous motivation, eight items) using a scale from one to five (not motivated - highly motivated). Students were allocated a score ranging from 0 to 20 for both controlled motivation (M = 8.31, SD = 3.13, Cronbach’s α = .87) and autonomous motivation (M = 15.05, SD = 2.37, Cronbach’s α = .86).

For vocational interests, we assessed students using the SIMON-I interest questionnaire that depicts students on a six dimensional, clockwise RIASEC model, reflecting their Realistic, Investigate, Artistic, Social, Enterprising and Conventional interests respectively (Fonteyne, Wille et al., 2017). Students had to respond to 152 items (yes or no), each loading on one of the six RIASEC scales. Items included professions like “Would you like to be a forester?” (loading on the R-scale) or activities like “Would you be interested in writing a scientific paper?” (loading on the I-scale). Students were scored from 0 to 100 on the R (M = 19.10, SD = 24.12, Cronbach’s α = .92) , I (M = 33.99, SD = 21.32, Cronbach’s α = .88), A (M = 28.78, SD = 25.13, Cronbach’s α = .92), S (M = 35.73, SD = 26.20, Cronbach’s α = .92), E (M = 33.54, SD = 28.28, Cronbach’s α = .93) and C (M = 21.33, SD = 22.96, Cronbach’s α = .90) dimensions. To validate our measurement of vocational interests we performed a randomization test of hypothesized order relations (RTOR, for a full discussion, see Tracey & Rounds, 1997). Results revealed a correspondence index of .92 and a significance of p = .02, indicating an excellent circular fit for the current data sample.

Next, we also derived two measures of person-environment fit (PE fit). PE fit reflects how well the interests of a student match the chosen program. *Euclidean distance* (M = 84.84, SD = 48.04) was calculated analogous to Wille and colleagues (2014), using P / T = 2 × R + I – A – 2 × S – E + C), D / I = (1.73× E + 1.73 × C − 1.73 × I − 1.73 × A) and Euclidean distance = SQRT ((student P / T – study program P / T)² + (student D / I – study program D / I)². Correlation fit (*M* = .71 , *SD* = .27) was calculated analogous to Schelfhout and colleagues (2021) by making the correlation between the RIASEC scores of the student and the RIASEC scores of the study program. As the present study will adopt a program-specific approach, all students within a specific program will study in the same environment. As a consequence, the RIASEC profile of the environment is identical for the students studying the same program. Due to this identical environment, it therefore becomes possible to also investigate the influence of the student's individual RIASEC dimensions on study success. For this reason, we have added both the individual dimensions as well as the fit measures to the pool of possible predictors.

For *conscientiousness* (*M* = 150.69, *SD* = 19.78, Cronbach's α = .88) we assessed students using the Personality for Professionals Inventory (De Fruyt & Rolland, 2010). Students had to respond to 48 items such as "I am more self-disciplined than most people" on a one to five scale (not characteristic at all – very characteristic).

For the related construct of *self-control* (*M* = 12.79, *SD* = 1.81, Cronbach's α = .74), we assessed students using the Brief Self-control Scale (Tangney et al., 2004). Students had to indicate on a one to five scale (totally not agree – totally agree) how much they agreed to statements (13) such as "I have difficulty concentrating". Total scores were rescaled to a score between 0 and 20.

For *metacognitive knowledge* (*M* = 13.61, *SD* = 2.07, Cronbach's α = .87) and *regulation* (*M* = 12.99, *SD* = 1.96, Cronbach's α = .92), students completed the Metacognitive Awareness Inventory (Schraw & Dennison, 1994). Students had to indicate on a one to six scale (completely disagree – completely agree) to which degree they agreed to 52 statements (17 for knowledge and 35 for regulation). Scores were rescaled to a score between 0 and 20. Items included statements like "I am good at remembering information".

For (cognitive) *test anxiety* (*M* = 10.02, *SD* = 2.46, Cronbach's α = .92), we assessed students using the Cognitive Test Anxiety Scale (Cassady & Finch, 2015). Students had to indicate on a one to four scale (totally not characteristic for me – totally characteristic for me) how characteristic they considered statements (25) such as " I am not good at taking exams". Total scores were rescaled to a score between 0 and 20.

For *academic self-efficacy comprehension* (*M* = 14.76, *SD* = 1.62, Cronbach's α = .80) and *academic self-efficacy effort* (*M* = 15.23, *SD* = 1.86, Cronbach's α = .74), we assessed students using an adaptation of the College Academic Self-Efficacy Scale (Owen & Froman, 1988). Students had to estimate their capability on a one to five scale (not at all capable – fully capable) of coping with situations or tasks (fourteen comprehension items and eight effort items) such as "taking multiple choice exams". Total scores were rescaled to a score between 0 and 20.

Non-equity adhering variables: family SES

We controlled for family SES as literature already shows that SES can have (unwanted) effects towards higher education (Calahan et al., 2018; Levine, 2011; Hanscombe, 2012). For the variable *scholarship*, university records indicated whether a student had received some form of funding (1) or not (0) due to a low family income. For *parental education*, students self-reported the degree of their parents (1 = at least one parent has obtained a bachelor degree; 0 = no parent has obtained a bachelor degree).

Procedure And Analyses

To start, we extract the basic skillsets by regressing the PASS variable on the predictors of academic achievement for each specific program. To decide which predictors are retained in the basic skillsets, we use a conservative AICc stepwise-selection procedure with correction for small sample sizes to select the best fitting model (Burnham & Anderson, 2002; Cavanaugh, 1997). Practically, this selection is made by comparing all possible predictor combinations (with linear and quadratic terms) against each other. Subsequently, the combination with the smallest chance of information loss is selected as the final basic skillset. This information loss is modeled by minimizing the (in-sample) prediction error for each (out-sample) student, which is the equivalent of a leave-one-out-cross-validation methodology. In such a methodology, a model is trained on all data minus the data for one specific student. The prediction of this trained model is then tested against the actual outcome (which was initially left out) for each specific student separately. The model that renders the smallest (out-sample) prediction error across all students is finally selected. This prediction error is crucial. Indeed, a classic explained variance (R^2) represents a model fit that only focuses on the in-sample error by comparing the regressed values to the original ones. In contrast, our prediction-specific model harbors the conservative cross-validation mechanism (i.e., based on the out-sample prediction error) discussed above to avoid overfitting data noise as an actual effect towards prediction (Shmueli, 2010). Although the resulting models are specifically designed towards individual student prediction, a Nagelkerke's pseudo – R^2 measure can still be used as an indication of model fit. To provide a general overview and to compare the results to literature, we have also calculated the frequency of all predictors across all selected models.

To predict study success for each individual student, we have first calculated the regression value for each individual student. Next, we have balanced the number of identified failing students (true positives) against the error rate (successful students predicted to be failing) through the use of a receiver operating characteristic curve or ROC curve on those regression values. Such a ROC curve balances the true positive rate (or sensitivity) versus the false positive rate or error rate (1 - true negative rate or 1 - specificity) for each program at different intervals. For the present study, we have used this ROC curve to establish the sensitivity (i.e., identified failing students) for all 21 specific program models across the false positive rate continuum of successful students identified as failing (i.e., error rate). Figure 1 presents an example of such a ROC-curve for one specific program. As a measure of how well the ROC-curve can distinguish passing and failing students in each program, the area under the curve (AUC) balances sensitivity and 1 – specificity. The AUC is calculated as an integral and is represented by a number between 1 (perfect accuracy) and .5 (distinction at chance level). AUC coefficients are usually labeled acceptable (.70 to .80), excellent (.80 to .90) or outstanding (above .90) in distinction model analyses (Hosmer & Lemeshow, 2000). For a full discussion on ROC and AUC analyses, we refer to Yonelinas and Parks (2007) and Fawcett (2006).

To illustrate the practical use of the current approach to predict academic achievement based on an assessment of basic cognition skills, we have also calculated the ratio and absolute number of failing and passing students that could end up in study counseling after receiving a warning about low chances of success. To summarize the average increase of identified failing students at increasing error rates across programs, we used equation (1) to fit the observed increase in identified failing students at increasing error rates. If our expectations are correct, we should observe that this curve displays the highest percentage of identified failing students at the lowest error rate, with higher error rates showing exponentially less additional identified failing students.

To control for family SES at the institutional level, the regression value from the program specific model for each student and the GPA-result for each student are regressed on both scholarship as well as parental education to provide an indication of unwanted bias by non-equity adhering variables on explained population variance for both study results as well as study orientation. To control for family SES at the individual student level, scholarship and parental education were also added to the pool of possible predictors to establish the prediction-specific model for each program.

Results

Table 2 shows the correlation matrix for all variables used. Results indicate that the vast majority of predictors are significantly related to academic achievement (GPA) across programs, barring some vocational interest variables. As we were primarily interested in program-specific (and not overall results) and prediction-specific (and not explanation-focused) analyses, we decided to act conservatively and retain these variables for further analysis, as different environments can demand a different basic skillset (Fonteyne, Duyck et al., 2017). Table 3 shows the final basic skillsets for all programs as determined by the AIC - procedure. For instance, the basic skillset for psychology indicates that students have to perform well in high school (predictor a) while also taking up sufficient weekly hours of mathematics (predictor c). Once at university, students should have a sufficient understanding of basic mathematics (predictor b), while also showing resilience against cognitive test anxiety (predictor d). If the combined result on these basic skills is not sufficient, a student could be invited for study counseling. The threshold for the combined result depends on the sensitivity (i.e., identified failing students) and specificity (error rate) parameters of the ROC curve for the specific program. The AUC statistic tied to the ROC curve indicates how well a program-specific basic skillset can distinguish passing and failing students. The AUC for most programs varied between AUC = .72 and AUC = .85, indicating an acceptable to excellent fit (Hosmer & Lemeshow, 2000). One outlier had a somewhat poor AUC = .65, while another outlier had an outstanding AUC = .91. Table 4 shows the percentage of identified failing students for each program across different error rates, based on the basic skillsets shown in Table 3. For instance, at a 5% error rate, Table 4 shows we are able to identify 27% of all failing psychology students. Combining the data from Tables 1 and 4, Table 5 shows us that 27% identified failing students (119.34) at a 5% error rate (19.60) leads to a ratio of about six to one in absolute student numbers that could receive an invitation for study counseling in the psychology program. In other words, for every six students at risk, one student who actually does not need study counseling is offered counseling advice months prior to failing (or in case of the one student, passing) exams. Moreover, Table 6 shows us that this ratio of six to one leads to an absolute number of 139 effective students being offered study counseling advice in the psychology program.

Figure 2 shows that the number of additional identified failing students across all programs decays rapidly at increasing error rates. A limited distribution of exponential decay managed to model this relation adequately (residual *SE* = 1.35 at 17 *df*), with the parameters *init*, *plateau* and *k* estimated at 2.32 ($p < .001$), 52.04 ($p < .001$) and 7.61 ($p < .001$) respectively. The turning point occurs at about the 20% error mark, at which point the gain in identifying failing students slows down dramatically. With this practical maximum error rate of 20%, we are able to identify an average of about 58% of all failing students across programs (see also Table 4). Moreover, at a prespecified 20% error rate, $n = 2791$ students would be invited for study counseling, of which $n = 2,316$ would eventually fail their exams, which is the equivalent of about 58% of all failing students (see also Tables 1, 5 and 6). Given these results, we have confirmed our initial hypothesis. We have indeed identified the majority of the students that lack the basic skills to succeed at lower error levels, months before these students would actually fail their exams.

Finally, Table 7 provides an overview of the frequency of all predictor categories across all selected models. Table 7 clearly shows the AIC procedure did not select scholarship or parental degree as a predictor for passing in any of the present study's program models. Furthermore, the linear regression of GPA on parental degree and scholarship was significant, F $(2, 5778) = 71.25$, $p < .001$, $R^2 = .024$, with both parental degree ($\beta = 0.12$, $p < .001$) as well as scholarship ($\beta = -0.07$, $p < .001$) reaching significance. Regarding population variance, we therefore conclude that family SES is related to academic achievement, although the effect is quite small. The linear regression of student specific model regression value on scholarship and parental degree was significant, F (2, 5778) = 29.69, $p < .001$, $R^2 = .010$, with both parental degree ($\beta = 0.063$, $p < .001$) as well as scholarship ($\beta = -0.064$, $p < .001$) reaching significance. Regarding population variance, we therefore conclude that family SES is still related to academic achievement prediction, although the effect is very minor and limited to about 1% of the variance in academic achievement. In sum, we thus conclude that the effect of family SES on the prediction of study results is nominal at best, with no practical implications for the prediction of individual study results.

Discussion

In an open access environment anyone with a high school degree can enter almost any program. Early knowledge about insufficient basic skills could prevent study failure and would improve the presently low program success rates in many Western-European higher education systems (Fonteyne, Duyck et al., 2017; Schelfhout et al., 2019). By identifying these students at risk of failing at the beginning of their model trajectory, an advice towards extra schooling or reorientation can instigate student action, either by pursuing basic skill development or by reorienting to a more appropriate program which better fits their basic skills altogether. As such, the present study investigated how accurately program-specific basic skill levels can predict study success in open access higher education. In doing so, the present study addressed two issues in literature. First, our study's prediction methodology regarding academic achievement primarily focused on a more appropriate prediction of individual student results, instead of the commonly used explanation of population variance in literature (Shmueli, 2010). And second, the extant literature focuses on determining the numbers of failing students (i.e., true positives) at very strict, but fixed false positive error rates across programs in open access education. In the present study, we explored the relation between these true and false positive rates using AIC, ROC and exponential decay analyses, using individual prediction approach on the basis of basic (non-) cognitive skills. As such, we identified more accurately how large the impact of a program-specific basic skillset actually is towards failing or passing. We also estimated how many students do not possess the basic skillset to succeed in a specific program at different error rates. This balance between accuracy and numbers of identified failing students will aid counselors and institutions in drawing out an appropriate and feasible counseling policy for specific students and specific programs.

As expected, the present study showed that nearly all (non-) cognitive and prior achievement predictors were significantly correlated with study success. Although the explained variance (i.e., an average of about 32% pseudo-variance across all logistic models) in academic achievement was not the primary focus of the present study, these findings do provide an additional validation of the present study's data as the patterns are largely in line with literature on academic achievement (Bandura, 1993; Credé & Kuncel, 2008; Duckworth et al., 2019; Hodara & Lewis, 2017; Kitsantas et al., 2008; Kriegbaum et al., 2018; Noble & Sawyer, 2002; Nye et al., 2018; Pinxten et al., 2017; Poole et al., 2012; Poropat, 2009; Rohde & Thompson, 2007; Roth et al., 2015; Ryan & Deci, 2017; Schneider & Preckel, 2017; Trapmann et al., 2007).

To predict individual student results, program-specific basic skillsets were linked to higher education study success of 6,624 students in open access study programs. These skillsets were drawn from a pool of (non-) cognitive predictors and prior achievements regarding study success using an AIC–regression procedure. Our basic skillset regressions showed that we could accurately identify about 58% of the students at risk of failing at relatively lower error rates (up to 20%), almost a year before they would actually drop out or fail their exams. Accepting even higher error rates (above 20%) would imply much less meaningful gains in the identification ratio of failing students, which should be avoided. These observations are in line with our formal representation of exponential decay, which showed a sufficient fit with our data and a clear turning point at the 20% error rate. Indeed, beyond this turning point, Accepting higher false positive error rates for study advice results in strongly declining rates of identified failing students and is therefore not warranted. Moreover, the AUC measures indicated that the present study succeeds in making a clear distinction between passing and failing students, based on program-specific basic skills. Important to note, high school GPA occurred in 95% of all program-specific models of the basic skillsets. As the OECD (2015, 2017) considers high school enrolment and subsequent degree attainment as the prime gateway towards acquiring basic skills and functional literacy, we consider the presence of high school GPA in nearly all basic skill models a good summary of acquired general basic skill of students when starting higher education. This general basic skill is then further supported by mainly (program-specific) cognitive skills and to a lesser extent also (program-specific) non-cognitive skills (Green, 2011; Kiely, 2014; Pierre et al., 2014; Schneider & Preckel, 2017) to adequately and accurately predict study success.

For the present study, family SES had a rather weak relation to higher education performance and orientation at the institutional level. In the present study's open-access environment, the family SES effect is limited to about 2.4 % of the explained variance in study results and to about 1% of the explained variance in orientation advice based on basic (non-) cognitive skills. This SES effect is very minor when compared to the reported relations between SES and cognitive ability of about r = .38 or about 15% of the explained variance (Cahalan et al., 2018; Levine, 2011; Hanscombe, 2012; Van den Broeck, 2014). Moreover, the present study's methodology renders the effect practically irrelevant towards prediction of individual student results and remediation or reorientation study advice for specific programs. These results are in line with the plea from literature to keep the effect of non-equity adhering variables as small as possible (Van Den Broeck, 2014). In sum, despite the well-documented relation in literature between SES and cognitive ability, the present study succeeds in relegating the effect of family SES to nominal at best. As such, orientation testing facilitates access to higher education as it monitors students in order for students to keep their access (and funding) towards higher education.

Theoretical Implications

To the best of our knowledge, the present study makes four major contributions to the literature regarding the prediction of study success. First, the present study adds to the scarce literature on the predictive value of basic skills towards higher education outcomes. This unique focus on the effects of basic (non-) cognitive skills complements the already large body of literature regarding the predictive value of advanced cognitive skills towards excellence in academic achievement (Schneider & Preckel, 2017). Second, as advocated by Schmueli (2010), we proposed a methodology with a program-specific focus that allows to predict individual student study success. By establishing a basic skillset for each program, we managed to correctly identify (to a large extent) those students that did not possess the basic skills needed to succeed in the first year of a bachelor program. Third, we explored the ratio between identified failing students (i.e., true positives) and the false positive error rate of students that are passing but were wrongfully categorized as failing. Knowledge of such a ratio allows to identify higher numbers of failing students, without overly inflating the error rate. And finally, the combination of open-access higher education, prior achievements and basic skill tests seems to be able to fully correct for family SES towards prediction of future study results. In other words, students are given advice towards remediation and reorientation based on their basic skills and not on their family SES, which adheres to the principle of equity (Heaslip et al., 2017; Jurado de los Santos et al., 2020).

These four theoretical contributions render better empirical results when comparing our study to previous studies on prediction of study success in open access higher education. For example, compared to Fonteyne, Duyck and colleagues (2017), our study identifies more than double the number of students at risk of failing (13% vs 29%) in a similar environment at equally strict error rates (5%). For sure, the addition of prior achievement in the prediction algorithms allows for a more powerful prediction tool. Exploring the balance between identifying failing students and more lenient error rates improves these results even further to more than three times the number of students at risk of failing at the cost of a minor increase in the error rate. Wielding such a specific approach when targeting the prediction of individual study success instead of an explanation of academic achievement variance therefore does seem warranted. Indeed, as Shmueli (2010) already suggested, explanation and prediction are in fact related, but far from identical applications of statistical modeling. For future educational and psychological studies, an assessment on the appropriate use regarding both applications of statistical modeling should therefore at least be considered. In other words, do we want to investigate the relation between a number of variables, or do we want to predict individual results?

Practical Implications

Our study also has implications for the professional practice of study counseling in open access higher education. Counselors who want to institute (conservative) evidence - based reorientation or remediation policies in an open access higher education context can use our methodology to establish which error rates for their specific situation are deemed acceptable and manageable for identifying students at risk using a program-specific basic skillset. As an example, the basic skillset for psychology consisted of prior achievements and hours of mathematics in high school and the performance on basic mathematics and cognitive test anxiety.

It is important to note that the basic skillsets should be considered as a whole, as shortages on one predictor can be remedied by a stronger performance on the other predictors. For instance, students can have a subpar score on the basic mathematics test due to circumstances, but still have a sufficient level of basic mathematics skill, further supported by good global results from high school and a resilience against test anxiety. Only if the combined results of these basic skill tests suggest that the student will fail, an advice to remedy or to reorient to a different program should be issued (Fonteyne, Duyck et al., 2017; Fonteyne et al., 2018). For instance, such an advice to remedy can target students that are prone to the effects of a specific predictor like test anxiety (Cassady & Finch, 2015). Counseling these students towards remedying their test anxiety, will also improve their global results on the other tests and subsequently also their exam results. As a second example, an advice towards reorientation can offer the student a second chance of choosing an appropriate study program. For instance, Schelfhout and colleagues (2021) have already suggested an empirical engine to match a student's vocational interests to a set of appropriate study programs.

To issue such advice, counselors can make use of any established predictive tests or variables available to them or even construct new tests that fulfill institution-specific needs towards very specific programs like for instance speech language and hearing science from the present study. Indeed, this program was captured somewhat less adequately by a basic skillset, although we still managed to identify about 40% of all failing students based on cognitive test anxiety alone. Such a program would really benefit from additional predictors. However, our proposed AIC - methodology will always ensure that the best possible model for prediction is extracted, based on the variables included. Given the adequate to excellent fit of the models and the number of identified students at risk, we are cautiously optimistic that this was in fact a good strategy.

Counselors should also consider their capacity and resources when suggesting remediation to students at risk. For instance, at a 5 % error rate, 139 psychology students are invited to study counseling. Counselors can consider a more lenient error rate of 10% if they can facilitate a maximum of no more than 216 students. Counselors should also address the cost of the error rate. At more lenient error rates the number of students (i.e., students that would pass at the end of the year) erroneously referred to the counselor's office will increase. However, tutoring still benefits these students as they did score subpar on the specific tests. Counselors should however be more cautious when offering reorienting or disengagement advice (Fonteyne et al., 2018), as they will also give faulty reorienting advice to a small number of students (depending on the error rate) that would eventually pass the program. Still, the (re)orientation advice in open access higher education is not binding and students can always opt to disregard the advice. It is therefore crucial that students are correctly informed about all modalities of the advice. In the exceptional case that both the AIC – procedure and the individual decision of a counselor both fail to recognize the potential of the student, the student always has the option to continue the curriculum and take the exams, with or without the aid of the offered tutoring. In other words, the consequences of a rare mistake do not have the gravitas of unrightfully refusing a student with high potential in a more closed selection context, where the decision of the counseling office is often binding and final. On a final note, counselors are also able to control their findings for unwanted effects towards equity if statistics on non-equity adhering variables are available.

Study Limitations And Research Opportunities

The present study has two limitations that provide an opportunity for further research. First, our study was conducted exclusively in an open access academic environment (Schelfhout et al., 2019). However, the AIC - prediction methodology with lenient and variable error rates can also be implemented in other international education systems that are more restricted or selection oriented, with even higher stakes towards higher education access. For this implementation, an adaptation of our presented method is required. The method should not extract basic skillsets, but skillsets that predict study excellence in specific programs (i.e., measured with instruments tailored towards excellence like the SAT or the ACT). The excellence skillset should also focus on identifying excellent students. For the error rate, two options exist. On the one hand, the institution can opt to use excellent students wrongfully identified as failing, if one wants to limit unrightfully excluding deserving students. On the other hand, the institution can opt to use failing students identified as successful, if the error rates have to vary in function of a *numerus clausus* (i.e., how many students can gain access to a specific program).

And second, the set of predictors for the present study was quite elaborate and representative of literature as indicated by the reported results. Future research should therefore ensure that the predictors used are sufficient in numbers and quality to extract adequate basic skillsets. At the moment, such datasets are unfortunately not readily available to institutions and counselors, which makes independent replication of our results quite arduous. Institutions and researchers should therefore start or continue to set up projects to enlarge our knowledge on identification of student success and failure.

Conclusion

The present study has demonstrated that we can accurately and adequately predict study failure in open access higher education using program-specific basic skillsets, while still adhering to the principles of equity in higher education. These basic skillsets are able to identify 58% of all failing students at lower error rates, months before these students would fail their exams. Individual students can make an evidence-based decision whether they want to follow remediation courses or change study program altogether. Institutions and study counselors can use the presented methodology to decide which and how many students need counseling towards remediation or reorientation depending on institution policy and needs.

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Tables and Figures

Table 1

Study Programs.

number	program	students	success rate	passing students	failing students
1	psychology	834	.47	392	442
2	communication science	189	.33	62	127
3	educational science	204	.62	126	78
4	political science	143	.31	44	99
5	law	264	.27	71	193
6	criminology	293	.31	91	202
7	speech language and hearing science	101	.55	56	45
8	linguistics	284	.47	133	151
9	history	112	.30	34	78
10	veterinary medicine	347	.28	97	250
11	rehabilitation science and physiotherapy	527	.28	148	379
12	pharmaceutical science	361	.48	173	188
13	bioscience engineering	377	.38	143	234
14	economical science	560	.45	252	308
15	biomedical science	229	.42	96	133
16	civil engineering	388	.52	202	186
17	business administration	450	.42	189	261
18	bioscience	118	.50	59	59
19	industrial engineering	515	.28	144	371
20	applied linguistics	219	.35	77	142
21	biochemistry and biotechnology	109	.40	44	65

Table 2

Correlation Matrix.

GPA	PASS	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	REA	INV	ART	SOC	ENT	CON
1	.75**	.41**	.16**	.19**	-.16**	.09**	.04**	.17**	.15**	.15**	.14**	.08**	.16**	.09**	-.01	.10**	.08**	.33**	.28**	-.05**	.03*	.02*	.09**	-.00	-.02
---	1	.34**	.15**	.15**	-.15**	.08**	.02*	.14**	.12**	.12**	.12**	.09**	.15**	.08**	-.01	.09**	.07**	.28**	.21**	-.05**	.03**	.02	.07**	.00	-.01
---	---	1	.13**	.10**	-.19**	.17**	.02	.28**	.11**	.14**	.21**	.16**	.24**	.03**	.01	.19**	.16**	.20**	.21**	-.03*	.09**	.05**	.04**	-.02	-.03*
---	---	---	1	.05**	-.04**	.11**	-.06**	.06**	.14**	.15**	.06**	.13**	.08**	-.01	-.04**	.09**	.010**	.29**	.15**	-.17**	.10**	.09**	.22**	-.22**	-.25**
---	---	---	---	1	-.08**	-.07**	.05**	.01	.06**	.05**	-.01	.22**	-.02	-.08**	.06**	.01	-.03**	.28**	.26**	.41**	.26**	-.18**	-.28**	-.07**	.05**
---	---	---	---	---	1	-.11**	.22**	-.29**	-.13**	-.11**	-.29**	-.37**	-.22**	.00	-.00	-.31**	-.14**	-.14**	-.13**	-.062*	-.03*	.04**	.12**	-.04**	-.01
---	---	---	---	---	---	1	.01	.44**	.05**	.07**	.33**	.35**	.46**	.11**	.01	.44**	.47**	.04	.12**	-.080*	.20**	.08**	.16**	.07**	.05**
---	---	---	---	---	---	---	1	-.08**	-.03**	-.02	-.16**	-.03*	-.08**	-.04**	.05**	-.03**	-.02*	.02	.04	.07**	.00	.02*	-.03**	.10**	.11**
---	---	---	---	---	---	---	---	1	.08**	.01	.73**	.37**	.59**	.12**	-.04**	.55**	.56**	.06**	.12**	-.04**	.12**	-.05**	.06**	.09**	.11**
---	---	---	---	---	---	---	---	---	1	.17**	.09**	.11**	.05**	.03**	.02	.09**	.08**	.21**	.17**	-.00	.02*	.03**	-.00	.02	.01
---	---	---	---	---	---	---	---	---	---	1	.00	.11**	.02	.01	.04**	.09**	.06**	.26**	.16**	-.00	.09**	.10**	.00	.01	-.06**
---	---	---	---	---	---	---	---	---	---	---	1	.23**	.51**	.12**	-.07**	.38**	.41**	.03	.07**	-.10**	.04**	-.05**	.07**	.01	.03**
---	---	---	---	---	---	---	---	---	---	---	---	1	.46**	-.00	.06**	.52**	.44**	.15**	.18**	.18**	.21**	-.00	-.05**	.08**	.08**
---	---	---	---	---	---	---	---	---	---	---	---	---	1	.11**	-.06**	.48**	.49**	.06**	.13**	-.08**	.08**	-.05**	.07**	-.03*	.02
---	---	---	---	---	---	---	---	---	---	---	---	---	---	1	-.51**	.10**	.11**	-.01	.01	-.30**	-.15**	-.16**	.10**	-.03*	-.13**
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	1	-.02	-.01	.07**	.05*	.28**	.23**	.29**	.09**	.23**	.26**
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	1	.77**	.09**	.13**	-.01	.13**	.03**	.07**	.07**	.04**
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	1	.08**	.12**	-.03**	.13**	.06**	.11**	.06**	.04**
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	1	.53**	.10**	.22**	.04	-.01	.02	.00
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	1	.09**	.24**	-.01	-.07**	.01	.04
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	1	.37**	.08**	-.24**	.12**	.23**
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	1	.16**	.17**	-.03**	.10**
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	1	.40**	.23**	.02*
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	1	.15**	.04**
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	1	.69**
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	1

Note. GPA = grade point average, PASS = passing all courses of the first year, a = high school GPA, b = mathematics, c = high school mathematics package, d = cognitive test anxiety, e = autonomous motivation, f = controlled motivation, g = conscientiousness, h = vocabulary, i = comprehensive reading, j = self-control, k = academic self-efficacy comprehension, l = academic self-efficacy effort, m = correlation fit, n = Euclidean distance, o = metacognition-knowledge, p = metacognition regulation, q = physics, r = chemistry, REA = realistic, INV = investigative, ART = artistic, SOC = social, ENT = enterprising, CON = conventional. With exception of PASS, a Pearson's product moment correlation coefficient was used. For PASS, a point-biserial correlation coefficient was used. $^{*}p < .05$, $^{**}p < .01$.

Table 3

Program-Specific Basic Skillsets.

program	model	R^2	AUC
1	$- 2.57 + 0.002 \times a^2 + 0.01 \times b^2 + 1.75 \times c - 0.16 \times c^2 - 0.18 \times a - 0.02 \times RE - 0.004 \times d^2$	.26	.75
2	$33.41 + 0.01 \times a^2 + 3.03 \times c - 0.0001 \times ENT^2 - 1.27 \times a - 0.27 \times c^2$	.30	.74
3	$- 20.5 + 0.15 \times a + 0.044 \times SOC - 0.00032 \times ENT^2 + 3.15 \times c - 0.3 \times c^2$	.29	.74
4	$- 11.76 + 0.00012 \times a^2 + 0.009 \times e^2 + 0.52 \times c + 0.024 \times ART$	.41	.81
5	$- 22.55 + 0.0021 \times a^2 + 3.38 \times c + 0.2 \times e - 0.29 \times c^2$	.48	.85
6	$- 9.61 + 0.00078 \times a^2 + 0.000088 \times g^2 + 0.16 \times b + 0.0052 \times f^2$	.23	.72
7	$1.69 - 0.012 \times d^2$	.10	.65
8	$- 9{,}91 + 0.0014 \times a^2 + 0.15 \times e$	.36	.80
9	$- 0.45 + 0.0018 \times a^2 + 0.018 \times h^2 - 0.38 \times b - 0.34 \times d + 0.6 \times k + 0.67 \times c$	.53	.85
10	$- 5.67 + 0.00061 \times a^2 + 0.12 \times q + 0.3 \times c - 0.12 \times d$	.26	.75
11	$- 8.56 + 0.0011 \times a^2 + 0.17 \times q$	.28	.77
12	$- 10.91 + 0.00085 \times a^2 + 0.28 \times b + 0.11 \times q$	.28	.75
13	$3.56 + 0.0032 \times a^2 + 0.0068 \times b^2 - 0.31 \times a$	.31	.76
14	$-16.35 + 0.2 \times a + 0.18 \times b$	.36	.80
15	$-15.41 + 0.14 \times a + 0.24 \times j + 0.12 \times e + 0.0045 \times q^2$	.31	.76
16	$- 12.55 + 0.13 \times a + 0.17 \times b$	.25	.74
17	$- 13.38 + 0.15 \times a + 0.14 \times b + 0.34 \times c$	.25	.75
18	$- 14.32 + 0.13 \times a + 0.54 \times c + 0.01 \times j$	.30	.75
19	$0.63 + 0.00015 \times a^2 + 0.021 \times b$	.13	.70
20	$- 9.43 + 0.0011 \times a^2 + 0.0059 \times b^2 + 0.094 \times i$	.31	.77
21	$- 8.74 + 0.0023 \times a^2 + 0.33 \times b + 0.51 \times r + 0.014 \times q^2 - 2.62 \times m^2$	.68	.91

Note. A student obtaining a PASS for his first year curriculum, has to individually pass all courses. The model is a logistic model, of which only the linear prediction element is shown. The explained population variance was measured through a Nagelkerke's (pseudo) R^2. The average R^2 amounted to 32%. The distinctive power of the model identifying failing from passing students is indicated by the Area Under the Curve (AUC). The order of the terms is displayed as originally rendered by the algorithm and represents the relative importance of the terms towards prediction. The terms can reflect linear effects, pure quadratic effects or curvilinear effects (linear +

quadratic effect). It is also possible that a term acts as a suppressor effect. For instance, *correlation fit* ^{2} in its own right has a positive effect on the passing rate, but can act as a suppressor for other effects in the model (negative effect). However, an individual breakdown of each model is beyond the scope of this study. GPA = grade point average, a = high school GPA, b = mathematics, c = high school mathematics package, d = cognitive test anxiety, e = autonomous motivation, f = controlled motivation, g = conscientiousness, h = vocabulary, i = comprehensive reading, j = self-control, k = academic self-efficacy comprehension, l = academic self-efficacy effort, m = correlation fit, n = Euclidean distance, o = metacognition-knowledge, p = metacognition regulation, q = physics, r = chemistry, REA = realistic, INV = investigative, ART = artistic, SOC = social, ENT = enterprising, CON = conventional. Programs: 1 = psychology, 2 = communication science, 3 = educational science, 4 = political science, 5 = law, 6 = criminology, 7 = speech language and hearing science, 8 = linguistics, 9 = history, 10 = veterinary medicine, 11 = rehabilitation science and physiotherapy, 12 = pharmaceutical science, 13 = bioscience engineering, 14 = economical science, 15 = biomedical science, 16 = civil engineering, 17 = business administration, 18 = bioscience, 19 = industrial engineering, 20 = applied linguistics, 21 = biochemistry and biotechnology.

Table 4

Identified Students At Risk Of Failing at Increasing Error Rates

ER/PN	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	ID
5%	27	17	22	45	43	21	9	40	31	25	31	27	28	29	36	21	26	16	25	26	66	29
10%	40	25	32	53	54	26	20	51	61	36	50	38	33	44	48	42	41	42	32	44	76	42
15%	49	31	46	65	68	44	27	59	71	52	57	48	39	57	59	47	47	49	41	52	78	52
20%	57	57	51	66	74	47	41	64	71	57	61	52	51	63	60	57	53	56	41	56	81	58
25%	61	63	54	72	75	53	48	66	80	61	66	59	59	68	64	62	60	61	51	61	83	63
30%	67	69	61	72	82	57	89	69	86	64	72	66	68	74	67	66	68	61	54	70	85	70
35%	70	71	63	77	87	61	61	75	87	69	72	68	78	82	72	71	72	72	60	77	90	73
40%	75	73	72	81	89	70	61	78	91	76	76	75	80	84	74	76	78	77	65	81	93	77
45%	77	78	78	85	91	77	66	82	91	78	81	80	83	88	78	79	79	79	74	84	95	81
50%	79	86	84	89	93	82	70	89	94	83	83	82	88	90	81	81	80	82	74	86	97	84
55%	83	86	87	91	93	86	73	90	94	85	85	88	89	91	83	84	82	86	83	87	100	87
60%	86	87	90	91	94	91	77	93	94	87	88	90	92	93	85	85	87	88	86	90	100	89
65%	88	89	93	92	94	92	80	93	94	89	91	91	92	95	87	88	90	91	88	92	100	91
70%	91	96	94	94	95	95	80	93	96	94	92	94	96	96	88	91	91	91	90	94	100	93
75%	94	96	96	96	98	96	89	96	96	94	96	96	97	97	94	94	93	93	93	95	100	95
80%	95	97	97	97	99	96	91	96	97	95	98	97	98	98	97	96	96	93	95	95	100	96
85%	97	98	99	98	100	97	91	97	99	96	98	99	98	99	98	98	96	93	96	95	100	97
90%	99	99	100	98	100	98	96	98	100	97	99	100	99	99	98	99	98	96	97	98	100	98
95%	99	99	100	98	100	100	98	99	100	98	99	100	100	99	100	100	99	100	99	99	100	99
100%	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Note. ER = error rate, PN = program number with 1 = psychology, 2 = communication science, 3 = educational science, 4 = political science, 5 = law, 6 = criminology, 7 = speech language and hearing science, 8 = linguistics, 9 = history, 10 = veterinary medicine, 11 = rehabilitation science and physiotherapy, 12 = pharmaceutical science, 13 = bioscience engineering, 14 = economical science, 15 = biomedical science, 16 = civil engineering, 17 = business administration, 18 = bioscience, 19 = industrial engineering, 20 = applied linguistics, 21 = biochemistry and biotechnology. For each program the number of additional identified failing students at increasing error rates is reported. ID = cumulative percentage of identified failing students at increasing error rates across programs.

Table 5

Identified Failing Students vs. Error Rate

ER/PN	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	R
5%	6.09	6.96	2.72	20.25	23.38	9.32	1.45	9.08	14.22	12.89	15.88	5.87	9.16	7.09	9.98	3.87	7.18	3.20	12.88	9.59	19.50	10.03
10%	4.51	5.12	1.98	11.93	14.68	5.77	1.61	5.79	13.99	9.28	12.80	4.13	5.40	5.38	6.65	3.87	5.66	4.20	8.24	8.11	11.23	7.16
15%	3.68	4.23	1.90	9.75	12.32	6.51	1.45	4.47	10.86	8.93	9.73	3.48	4.25	4.64	5.45	2.89	4.33	3.27	7.04	6.39	7.68	5.87
20%	3.21	5.84	1.58	7.43	10.06	5.22	1.65	3.63	8.14	7.35	7.81	2.83	4.17	3.85	4.16	2.62	3.66	2.80	5.28	5.16	5.98	4.88
25%	2.75	5.16	1.34	6.48	8.15	4.71	1.54	3.00	7.34	6.29	6.76	2.56	3.86	3.32	3.55	2.28	3.31	2.44	5.26	4.50	4.90	4.26
30%	2.52	4.71	1.26	5.40	7.43	4.22	2.38	2.61	6.58	5.50	6.15	2.39	3.71	3.01	3.09	2.03	3.13	2.03	4.64	4.30	4.19	3.87
35%	2.26	4.16	1.11	4.95	6.76	3.87	1.40	2.43	5.70	5.08	5.27	2.11	3.65	2.86	2.85	1.87	2.84	2.06	4.42	4.06	3.80	3.50
40%	2.11	3.74	1.11	4.56	6.05	3.88	1.23	2.21	5.22	4.90	4.87	2.04	3.27	2.57	2.56	1.75	2.69	1.93	4.19	3.73	3.43	3.24
45%	1.93	3.55	1.07	4.25	5.50	3.80	1.18	2.07	4.64	4.47	4.61	1.93	3.02	2.39	2.40	1.62	2.42	1.76	4.24	3.44	3.12	3.02
50%	1.78	3.52	1.04	4.01	5.06	3.64	1.13	2.02	4.31	4.28	4.25	1.78	2.88	2.20	2.24	1.49	2.21	1.64	3.81	3.17	2.87	2.83
55%	1.70	3.20	0.98	3.72	4.60	3.47	1.07	1.86	3.92	3.98	3.96	1.74	2.65	2.02	2.09	1.41	2.06	1.56	3.89	2.92	2.69	2.64
60%	1.62	2.97	0.93	3.41	4.26	3.37	1.03	1.76	3.59	3.74	3.76	1.63	2.51	1.89	1.96	1.30	2.00	1.47	3.69	2.77	2.46	2.48
65%	1.53	2.80	0.89	3.18	3.93	3.14	0.99	1.62	3.32	3.53	3.59	1.52	2.32	1.79	1.85	1.25	1.91	1.40	3.49	2.61	2.27	2.33
70%	1.47	2.81	0.83	3.02	3.69	3.01	0.92	1.51	3.15	3.46	3.37	1.46	2.24	1.68	1.74	1.20	1.80	1.30	3.31	2.48	2.11	2.22
75%	1.41	2.62	0.79	2.88	3.55	2.84	0.95	1.45	2.94	3.23	3.28	1.39	2.12	1.58	1.74	1.15	1.71	1.24	3.19	2.34	1.97	2.11
80%	1.34	2.48	0.75	2.73	3.36	2.66	0.91	1.36	2.78	3.06	3.14	1.32	2.00	1.50	1.68	1.10	1.66	1.16	3.06	2.19	1.85	2.00
85%	1.29	2.36	0.72	2.59	3.20	2.53	0.86	1.30	2.67	2.91	2.95	1.27	1.89	1.42	1.60	1.06	1.56	1.09	2.91	2.06	1.74	1.90
90%	1.24	2.25	0.69	2.45	3.02	2.42	0.86	1.24	2.55	2.78	2.82	1.21	1.80	1.34	1.51	1.01	1.50	1.07	2.78	2.01	1.64	1.82
95%	1.18	2.13	0.65	2.32	2.86	2.34	0.83	1.18	2.41	2.66	2.67	1.14	1.72	1.27	1.46	0.97	1.44	1.05	2.68	1.92	1.56	1.74
100%	1.13	2.05	0.62	2.25	2.72	2.22	0.80	1.14	2.29	2.58	2.56	1.09	1.64	1.22	1.39	0.92	1.38	1.00	2.58	1.84	1.48	1.66

Note. ER = error rate, PN = program number, with 1 = psychology, 2 = communication science, 3 = educational science, 4 = political science, 5 = law, 6 = criminology, 7 = speech language and hearing science, 8 = linguistics, 9 = history, 10 = veterinary medicine, 11 = rehabilitation science and physiotherapy, 12 = pharmaceutical science, 13 = bioscience engineering, 14 = economical science, 15 = biomedical science, 16 = civil engineering, 17 = business administration, 18 = bioscience, 19 = industrial engineering, 20 = applied linguistics, 21 = biochemistry and biotechnology. For each program the ratio is reported between correctly identified failing students vs. the error rate at increasing error rates. R = average ratio of correctly identified failing students vs. the error rate at increasing error rates over programs.

Table 6

Number of Students Offered Study Counseling

ER/PN	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	NR
5%	139	25	23	47	87	47	7	67	26	67	125	59	73	102	53	49	77	12	100	41	45	1271
10%	216	38	38	57	111	62	15	90	51	100	204	89	92	161	73	98	126	31	133	70	54	1908
15%	275	49	55	71	142	103	21	109	60	145	238	116	113	213	93	118	151	38	174	85	57	2425
20%	330	85	65	74	157	113	30	123	62	162	261	132	148	244	99	146	176	45	181	95	61	2791
25%	368	96	74	82	163	130	36	133	71	177	287	154	174	272	109	166	204	51	225	106	65	3141
30%	414	106	85	84	180	142	57	144	77	189	317	176	202	304	118	183	234	54	244	123	68	3502
35%	447	112	93	92	193	155	47	160	80	206	325	188	233	341	129	203	254	63	273	136	74	3803
40%	488	118	107	98	200	178	50	171	85	229	347	210	244	360	137	222	279	69	299	146	78	4114
45%	517	127	118	104	208	196	55	184	86	239	374	228	259	384	147	238	291	73	339	154	82	4402
50%	545	140	129	110	215	211	60	201	90	256	389	241	277	403	156	252	303	78	347	161	85	4648
55%	582	143	137	114	219	224	64	209	92	266	404	261	287	419	163	267	318	83	387	166	89	4894
60%	615	148	146	116	224	238	68	220	94	276	422	273	301	438	171	279	340	87	405	174	91	5128
65%	644	153	154	120	228	245	72	227	95	286	441	284	308	456	178	295	358	92	420	181	94	5331
70%	677	165	162	124	233	256	75	234	99	303	452	298	325	472	184	311	370	95	435	187	96	5551
75%	709	168	169	128	242	262	82	245	100	308	475	310	334	488	197	326	384	99	453	193	98	5772
80%	734	173	176	131	248	267	86	251	103	315	490	321	344	503	206	340	402	102	468	197	100	5956
85%	762	177	184	134	253	273	89	260	106	322	497	333	351	519	212	354	411	105	479	200	102	6125
90%	790	182	191	137	257	280	94	268	109	330	508	344	360	532	217	366	426	110	489	208	105	6301
95%	810	185	198	139	260	288	97	276	110	337	516	352	370	544	224	378	438	115	504	214	107	6463
100%	834	189	204	143	264	293	101	284	112	347	527	361	377	560	229	388	450	118	515	219	109	6624

Note. ER = error rate, PN = program number, with 1 = psychology, 2 = communication science, 3 = educational science, 4 = political science, 5 = law, 6 = criminology, 7 = speech language and hearing science, 8 = linguistics, 9 = history, 10 = veterinary medicine, 11 = rehabilitation science and physiotherapy, 12 = pharmaceutical science, 13 = bioscience engineering, 14 = economical science, 15 = biomedical science, 16 = civil engineering, 17 = business administration, 18 = bioscience, 19 = industrial engineering, 20 = applied linguistics, 21 = biochemistry and biotechnology. The number of students that is offered study counseling is calculated from the number of actual passing (error rate) and failing students that are identified as failing at increasing error rates. NR = total number of students offered study counseling across programs.

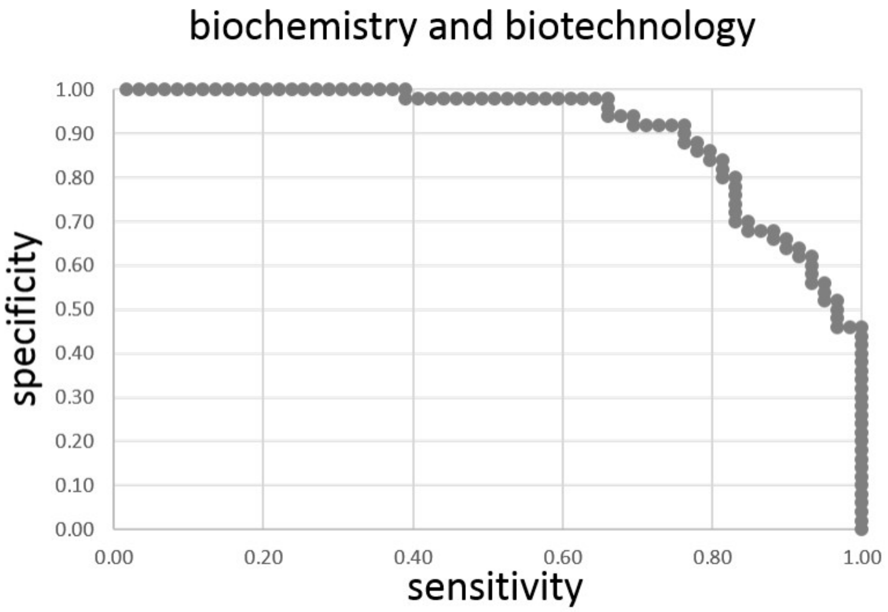
Table 7

Frequency Of Predictor Categories across Program Specific Models

program	prior achievement	cognitive ability	motivation	vocational interest	cognitive test anxiety	conscientiousness	academic self-efficacy	metacognition	family SES
psychology	1	1	0	1	1	0	0	0	0
communication science	1	0	0	1	0	0	0	0	0
educational science	1	0	0	1	0	0	0	0	0
political science	1	0	1	1	0	0	0	0	0
law	1	0	1	0	0	0	0	0	0
criminology	1	1	1	0	0	1	0	0	0
speech language and hearing science	0	0	0	0	1	0	0	0	0
linguistics	1	0	1	0	0	0	0	0	0
history	1	1	0	0	1	0	1	0	0
veterinary medicine	1	1	0	0	1	0	0	0	0
rehabilitation science and physiotherapy	1	1	0	0	0	0	0	0	0
pharmaceutical science	1	1	0	0	0	0	0	0	0
bioscience engineering	1	1	0	0	0	0	0	0	0
economical science	1	1	0	0	0	0	0	0	0
biomedical science	1	1	1	0	0	1	0	0	0
civil engineering	1	1	0	0	0	0	0	0	0
business administration	1	1	0	0	0	0	0	0	0
bioscience	1	0	0	0	0	1	0	0	0
industrial engineering	1	1	0	0	0	0	0	0	0
applied linguistics	1	1	0	0	0	0	0	0	0
biochemistry and biotechnology	1	1	0	1	0	0	0	0	0
impact	0.95	0.67	0.24	0.24	0.19	0.14	0.05	0.00	0.00

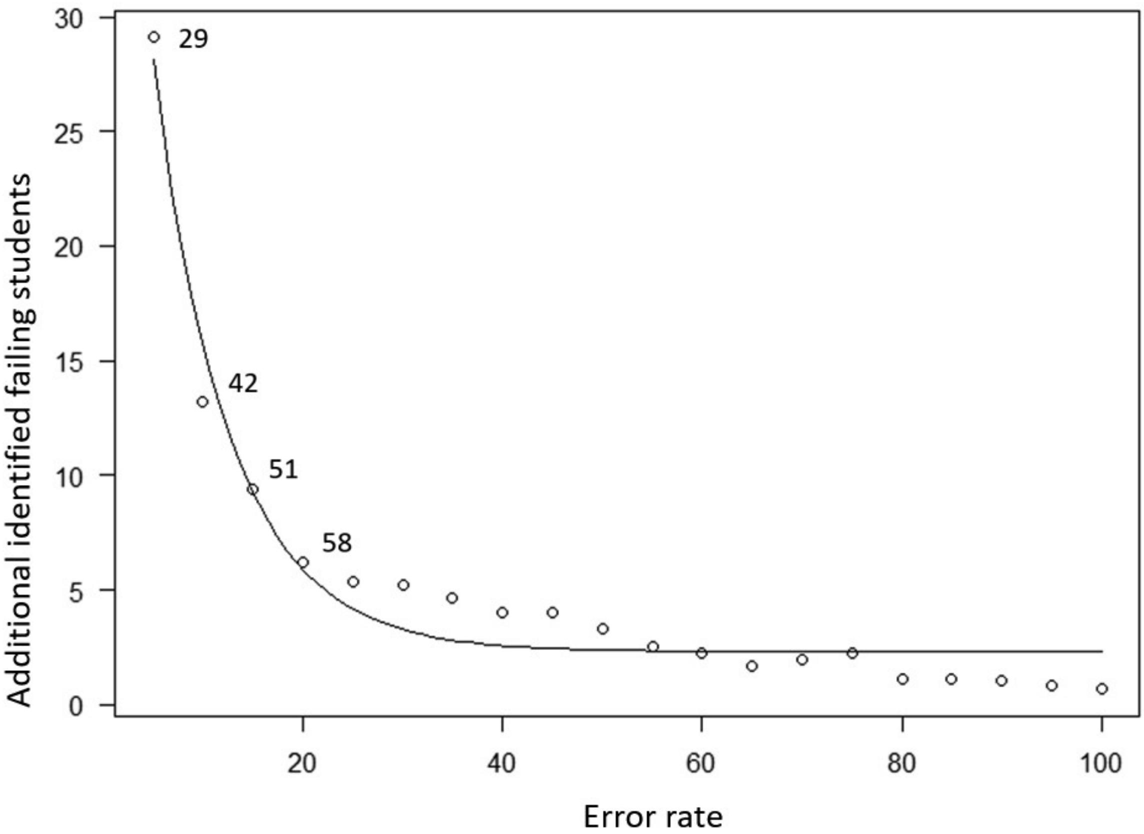
Note. The predictors were pooled as presented in the method section. As such, prior achievement = high school GPA and high school mathematics package; cognitive ability = vocabulary, comprehensive reading, mathematics, chemistry and physics; motivation = autonomous and controlled motivation; vocational interest = RIASEC dimensions, Euclidean distance and correlation fit; cognitive test anxiety; conscientiousness = conscientiousness and self-control; academic self-efficacy = comprehension and effort; metacognition = knowledge and regulation; SES = social-economic status. Predictor categories are marked 1 if a predictor from that category occurs in the predictive model of the specific program. The *impact* indicates the relative frequency across programs of the predictor category.

Figure 1. ROC Curve for the Program *biochemistry and biotechnology*.



Note. Sensitivity indicates the proportion true positives, or failing students correctly identified as failing. Specificity indicated the proportion true negatives, or passing students correctly identified as passing. The error rate represents passing students erroneously identified as failing, or error rate = 1-specificity. The Area Under the Curve (AUC) indicates how well the model can distinguish between passing and failing students. For this specific model, the AUC amounts to 91%.

Figure 2. Decrease in Additional Identified Failing Students at Increasing Error Rates.



Note. The number of additional identified failing students over programs is depicted in hollow, the exponential decay regression line is depicted in full. As an example, at a 5% error rate, 29% of the failing students is identified. At 10% error rate, an additional 13% of the failing students is identified, totaling 42% identified failing students. The upper limit (init) was estimated at an error rate value of 2.32, the plateau was reached after an error rate value of 52.04 and the steepness of decay was estimated at 7.61, with the largest decay occurring between the error rates of 5% and 20%. Indeed, at a 20% error rate a clear turning point is observed, with only marginal additions of identified failing students occurring hereafter.