To fail or not to fail?
Identifying students at risk by predicting academic success

Fonteyne Lot, De Fruyt Filip, Duyck Wouter

Abstract

Student attrition problems are manifest worldwide. Therefore, the identification of students at risk of failure is of major importance. In the current study several cognitive and non–cognitive factors are evaluated in terms of predictive power for failure in the first year of university. Next, a model is proposed that can predict who passes and thus identifies students at risk for academic failure. The sample consists of 461 newly enrolled students in psychology and educational sciences programs. Educational background variables were retrieved from the university database and several cognitive (mathematics skills, reading comprehension and vocabulary knowledge) and non–cognitive (motivation and self–efficacy) measures were administered at the start of the academic year. Logistic regression analysis was used to predict first year academic. Four predictors prove relevant for identification of students at risk of not passing the first year: academic self–efficacy, hours of mathematics instruction in secondary education, results on a basic mathematics test and vocabulary knowledge. A model containing these factors identifies 25% of failing students, while maintaining a specificity of 98%. The practical implications of these results are manifold. First, they help identifying at–risk students. Moreover, they are helpful in designing intervention strategies for those at–risk students. Lastly, they serve as a basis for the development of an online tool that helps future students evaluate their cognitive and non–cognitive abilities in order to choose a major that best suits their potential and background.

Key words: Academic success, predict, non–cognitive, cognitive, performance.

1. Introduction

Participation to higher education is on the rise worldwide, but there is considerable room for improvement in graduation rates. Student
Attrition problems are manifest worldwide. The OECD (2013) reported that 32% of tertiary students did not graduate from a program at this level. In Flanders, a mere 40% of the university students pass all courses during the first year of studying. This is alarming, even more so since first year performance is one of the best predictors of academic retention (de Koning, Loyens, Rikers, Smeets, & van der Molen, 2012; Murtaugh, Burns, & Schuster, 1999).

High drop-out and low success rates in undergraduates demonstrate the continuing importance of the search for factors influencing academic achievement in post-secondary education. This is especially relevant in regions such as Flanders, where there is an open access policy in higher education. There are no entrance exams and a secondary education degree is sufficient to enroll in almost any higher education program. As a consequence, attrition rates are high and institutions pursue the early identification of students at risk of failure.

Cognitive factors and academic success

Historically, cognitive factors have dominated the study of academic achievement. This is not surprising as the first broad test of cognitive ability was specifically designed to predict achievement in an educational context (Brody, 2000). Since then, studies have consistently shown that cognitive ability predicts academic achievement (Ackerman & Heggestad, 1997; Busato, Prins, Elshout, & Hamaker, 2000; Farsides & Woodfield, 2003; Kuncel & Hezlett, 2010). As a result, it is mainly cognitive ability that is tested for admission decisions in countries with restricted access to higher education. Most of these tests assess a combination of verbal and quantitative skills (Sedlacek, 2011). Hence, we include both verbal and quantitative measures in the current study.

Non-cognitive factors and academic success

Cognitive ability measures remain important, but research shows that correlations between ability measures and academic performance are lower at more advanced levels of education (Boekaerts, 1995). Thus, recently there is a shift in focus towards non-cognitive factors. This research is growing steadily and supports the contribution of these fac-
tors to the prediction of academic success (Allen, Robbins, & Sawyer, 2009; Robbins, Allen, Casillas, Peterson, & Le, 2006; Shivpuri, Schmitt, Oswald, & Kim, 2006). For example, studies show that academic outcomes can be predicted by personality (Conard, 2005; O’Connor & Paunonen, 2007; Poropat, 2009; Trapmann, Hell, Hirn, & Schuler, 2007), study skills (Credé & Kuncel, 2008) and motivation (Komarraju, Karau, & Schmeck, 2009).

Robbins et al. (2004) conducted a meta–analysis of 109 studies on the relationship between non–cognitive constructs and college outcomes. They found that, on top of the cognitive factors, the strongest predictors for GPA were academic self–efficacy and achievement motivation. This led us to add these factors to the current study.

Self–efficacy was originally defined by Bandura (1997). In short, it is “the belief in the ability to succeed”. Research shows that more specific measures of self–efficacy have better results in the prediction and explanation of related outcomes (Choi, 2005; Pajares, 1996). Hence, we are especially interested in academic self–efficacy. Numerous studies provide evidence for the relation between academic self–efficacy and academic performance (Chemers, Hu, & Garcia, 2001; Elias & Loomis, 2002; Lent, Brown, & Larkin, 1986).

Motivation was investigated from a self–determination perspective (Ryan & Deci, 2000) which discriminates between two broad forms of motivation that lie on a continuum: autonomous motivation versus controlled motivation. Autonomous motivation is believed to have more desirable outcomes on academic success (Komarraju et al., 2009; Vansteenkiste, Zhou, Lens, & Soenens, 2005).

**Background variables and academic success**

Two background variables are included in the analysis because of their presumed predictive value: educational background and gender.

Large differences in passing rates are found between students with different educational backgrounds. In Flanders, students from secondary education programs with a higher emphasis on mathematics systematically obtain better results in higher education (Declercq & Verboven, 2010; Rombaut, 2006). On that account, we included the variable “hours of mathematics instruction in secondary education” as a proxy for educational background.
Gender is also included in the study since women nowadays outperform males in college entry and completion (Buchmann, DiPrete, & McDaniel, 2008).

The aim of the current study is twofold. First, we want to evaluate the predictive power of cognitive, non-cognitive and several background factors for failure in the first year of university. Second, we are in search of a model that predicts who passes and thus identifies students at risk for academic failure.

2. Method

Procedure and participants

Students were given paper–and–pencil versions of the basic mathematical skills test in the first statistics class of the academic year. Other tests were administered online in the course of the first semester. Only data of new incoming undergraduate students in the fields of psychology and educational sciences were analyzed. The sample consisted of 461 respondents. The dataset was randomly divided into a training set of approximately 75% of the cases ($N=337$) and a validation set containing the other 25% ($N=124$).

Measures

*Basic mathematic skills* were measured by an instrument designed specifically to identify at–risk students. Since it is our intention to discriminate at the low end of the distribution, basic mathematic operations rather than highly difficult mathematical problems were included. The test consists of 20 items measuring operations such as the rule of three and operations with brackets.

*Reading comprehension* consists of an English text with 5 multiple choice questions. This text was previously validated and used in the Swedish Scholastic Aptitude Test.

*Vocabulary knowledge* was administered with the LexTALE (Lemhöfer & Broersma, 2012). Respondents are asked to indicate whether 40
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words and 20 non-word are correct Dutch words or not. The resulting score is an indication of general Dutch proficiency.

For Motivation, the “Zelfregulatie Vragenlijst Leren” (Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009) was administered. This is a translated and adapted version of the Academic Self-Regulation Questionnaire (Ryan & Connell, 1989). Respondents indicate on a 5-point Likert scale to what extent they agree with different reasons for studying. Items for controlled (e.g., “because I’m supposed to do so”) and autonomous motivation (e.g., “because I want to learn new things”) are included. The Relative Autonomy Index (RAI) is used to measure the strength of self-determined study motivation. This measure combines scores on all subtypes of motivation and has been used on other occasions (see e.g., Vallerand, Fortier, & Guay, 1997; Vansteenkiste et al., 2005).

Academic self-efficacy was measured by an adapted version of the College Academic Self Efficacy Scale by Owen and Froman (Owen & Froman, 1988). Since “social” academic aspects such as “talking to a professor privately to get to know him or her” do not or to a lesser extent apply to undergraduate programs at universities in Flanders, these items were excluded from the original scale. Students use a 5-point Likert scale to indicate their confidence to execute 22 typically academic behaviors such as “writing a high quality term paper”.

Background variables gender and hours of mathematics in secondary education were retrieved from the university database.

The Outcome variable is “passing the first year successfully”. Results were retrieved from university database. Students who dropped out before the end of the academic year were categorized as “failed”.
3. Results

Descriptive statistics and group differences are shown in Table 1.

Table 1. Descriptive statistics and differences between failed and passed students.

<table>
<thead>
<tr>
<th></th>
<th>Failed</th>
<th>Mean</th>
<th>SD</th>
<th>Passed</th>
<th>Mean</th>
<th>SD</th>
<th>Effect size Cohen’s d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mathematics test score</td>
<td>14.07</td>
<td>3.32</td>
<td></td>
<td>16.28</td>
<td>2.91</td>
<td>0.71</td>
<td></td>
</tr>
<tr>
<td>Reading comprehension</td>
<td>3.23</td>
<td>1.19</td>
<td></td>
<td>3.36</td>
<td>1.13</td>
<td>0.11</td>
<td></td>
</tr>
<tr>
<td>Vocabulary knowledge</td>
<td>17.69</td>
<td>1.50</td>
<td></td>
<td>18.20</td>
<td>1.04</td>
<td>0.39</td>
<td></td>
</tr>
<tr>
<td>Motivation</td>
<td>3.48</td>
<td>3.11</td>
<td></td>
<td>4.17</td>
<td>2.87</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td>Academic self–efficacy</td>
<td>13.86</td>
<td>1.49</td>
<td></td>
<td>14.93</td>
<td>1.55</td>
<td>0.70</td>
<td></td>
</tr>
<tr>
<td>Gender (Male=1; Female =2)</td>
<td>1.87</td>
<td>0.33</td>
<td></td>
<td>1.91</td>
<td>0.28</td>
<td>0.13</td>
<td></td>
</tr>
<tr>
<td>Hours of math instruction in secondary education</td>
<td>3.20</td>
<td>1.52</td>
<td></td>
<td>4.19</td>
<td>1.65</td>
<td>0.63</td>
<td></td>
</tr>
</tbody>
</table>

Evaluation of predictive power

To evaluate the predictive power of explanatory factors for failure in the first academic year, recursive feature elimination was applied to the testing set. This is a logistic regression that follows the backward stepwise procedure and is embedded in a K-fold cross-validation. Cross-validation was performed on 10 subsets and was repeated 3 times. Analysis shows that a model with four variables has the highest average accuracy (.71). The four variables with incremental predictive value are academic self–efficacy, hours of mathematics in secondary education, mathematics test score and vocabulary knowledge. Although hours of mathematics instruction in secondary education significantly correlated with mathematics test score, there was no problem of multicolinearity (VIF < 10) (Field, 2009).

Cross–validation of predictive model

Next, we build a regression model consisting of the identified factors and used cross–validation for evaluation. Parameter estimates of the logistic regression model (as seen in Table 2) were forced onto the validation sample.
Table 2. Parameter estimates and model specifications in the testing set.

<table>
<thead>
<tr>
<th></th>
<th>B (SE)</th>
<th>Lower Odds Ratio</th>
<th>Upper Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-15.167* (2.697)</td>
<td>1.326</td>
<td>1.573</td>
</tr>
<tr>
<td>Academic self–efficacy</td>
<td>.453* (.087)</td>
<td>1.142</td>
<td>1.367</td>
</tr>
<tr>
<td>Hours of mathematics in Secondary Education</td>
<td>.313* (.092)</td>
<td>1.209</td>
<td>1.209</td>
</tr>
<tr>
<td>Mathematics test score</td>
<td>.190* (.045)</td>
<td>.993</td>
<td>1.256</td>
</tr>
<tr>
<td>Vocabulary knowledge</td>
<td>.228 (.120)</td>
<td>.993</td>
<td>1.256</td>
</tr>
</tbody>
</table>

R² = .34 (Nagelkerke), Model \( \chi^2 = 95.18, p < .01 \) * p < .01

Tabel 3 shows the diagnostic values of the model in the validation sample. Overall classification succes was 69.4% with an Area Under the Curve (AUC) of .73. A cut–score of .50 is standard, but does not serve our aim. We are rather in search of a cut–score that allows us to identify students at risk of failure, without wrongfully classifying passing students. Thus, high specificity is essential. For this purpose the cut–score was set to .13. Diagnostic values of the model at cut–score.13 are also shown in Table 3. At this cut–score we are able to identify 25% of failing students with a specificity of 98%.

Table 3. Diagnostic values of the predictive model in the validation sample at different cut–scores.

<table>
<thead>
<tr>
<th></th>
<th>Cut–score .50</th>
<th>Cut–score .13</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>82.89%</td>
<td>25%</td>
</tr>
<tr>
<td>Specificity</td>
<td>47.92%</td>
<td>97.92%</td>
</tr>
<tr>
<td>Positive predictive value</td>
<td>71.59%</td>
<td>95%</td>
</tr>
<tr>
<td>Negative predictive value</td>
<td>63.89%</td>
<td>45.19%</td>
</tr>
<tr>
<td>Overall Accuracy</td>
<td>69.4%</td>
<td>54%</td>
</tr>
<tr>
<td>Area Under the Curve</td>
<td>.73</td>
<td>.73</td>
</tr>
</tbody>
</table>

4. Discussion

Hours of mathematics in secondary education, vocabulary knowledge and score on the mathematics test contribute to the prediction of first
year academic success. This is in accordance with well established admission tests such as the SAT and ACT, which measure verbal and math ability and are in essence general intelligence tests (Sedlacek, 2010). Our results show that even basic skills tests can tackle the cognitive ability needed in higher education.

Academic self-efficacy was the strongest predictor of first year academic success. This is in line with previous research and supports the importance of non-cognitive variables for the prediction of academic success. Reading comprehension and motivation as measured from a self-determination perspective did not have incremental explanatory power. Neither did gender.

The practical implications of these results are manifold. First, identification of 25% of the students who do not pass the first year makes it possible to proactively stimulate them to subscribe for remedial courses. Moreover, intervention strategies can be designed in accordance with these results. For example, sessions can be organized in which basic mathematic skills are trained. Also, study skills sessions can augment academic self-efficacy because training students to develop successful learning strategies may increase their confidence in their abilities (Komarraju et al., 2009).

Lastly, the results serve as a basis for the development of an online tool that helps future students evaluate their cognitive and non-cognitive abilities in order to choose a major that best suits their potential and background. This way, detection takes place even before enrollment, which spares potential students the motivational and financial costs of not passing.

There are several limitations to our study. First, we operationalized the outcome variable as a dichotomous pass-fail while the reality is more complex. Since the Bologna declaration, flexibility in trajectories has increased enormously. Therefore, a more longitudinal approach in which graduation serves as outcome variable is more in order. Nevertheless, first year academic performances has been documented as a powerful predictor of overall academic achievement (de Koning et al., 2012) and retention (Murtaugh et al., 1999). Next, our study was limited to majors in psychology and educational sciences. It is yet to be established whether these results can be generalized to other fields of study. Lastly, other factors have been shown to contribute to the prediction of academic achievement, such as study skills (Credé &
Kuncel, 2008) and test anxiety (Cassady & Johnson, 2002). Personality has also been thoroughly studied in relation to academic achievement. Especially the Big Five factor conscientiousness shows incremental validity for predicting academic success (Conard, 2005; Noftle & Robins, 2007; Poropat, 2009; Trapmann et al., 2007).

The addition of these factors might increase specificity of the model.

5. Conclusion

This study shows that we can identify students at risk of failure in the first academic year with relatively few predictors. At the start of the academic year, we can identify 25% of the failing students with a specificity of 98%.

References


