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Predicting Academic Performance in Engineering Using High School Exam Scores*

J. C. F. DE WINTER and D. DODOU
Department of BioMechanical Engineering, Faculty of Mechanical, Maritime and Materials Engineering, Delft University of Technology, The Netherlands. E-mail: j.c.f.dewinter@tudelft.nl

This study investigated the extent to which high school exam scores predict first-year grade point averages (GPA) and completion of Bachelor of Science (B.Sc.) programs at a Dutch technical university. It was hypothesized that, of the exam scores, those for mathematics and physics would be the strongest predictors of academic performance. Factor analysis of high school exam scores was performed for a cohort of 1,050 students. Regression analysis of the extracted factors was conducted to predict first-year GPA and B.Sc. completion. The results showed that the Natural Sciences and Mathematics factor (loading variables: physics, chemistry, and mathematics) was the strongest predictor of first-year GPA and B.Sc. completion, the Liberal Arts factor was a weak predictor, and the Languages factor had no significant predictive value. Differences were identified across the B.Sc. programs, with programs that relied strongly on Natural Sciences and Mathematics enrolling better-performing students. Women entered university with higher average exam scores than men, but gender was not predictive of first-year GPA and was a weak predictor (with an advantage for women) of B.Sc. completion. These findings may prove valuable in the development of predictors of academic performance in engineering.

Keywords: engineering; academic performance; predictors; natural sciences; mathematics.

1. Introduction

Being able to predict academic performance is important as it allows us to identify those students who are most likely to complete their studies successfully and on time. Enrolling under-qualified students in a university constitutes a misuse of resources, whereas failing to recruit the most able candidates weakens a discipline in the long term.

It is possible to make a distinction between cognitive and non-cognitive predictors of academic performance [1–4]. Cognitive predictors can be general abilities that define aptitude for learning (measured with intelligence tests or standardized aptitude tests, such as the SAT Reasoning Test and the Miller Analogies Test [5–7]), or domain-specific predictors of educational achievement (e.g., the SAT Subject Tests, the Pharmacy College Admission Test, and individual secondary education course grades [8–10]). There is an ongoing discussion concerning the usefulness of domain-specific predictors versus general ability predictors in relation to educational outcomes [11]. Self-efficacy has also been recognized as an aspect of human cognition that is vitally important for success in academia [12–14].

Non-cognitive (i.e., affective and conative) constructs as predictors of academic success have also been investigated, where affective covers emotional reactions, and conative refers to motivational and volitional processes [15, 16]. Successful examples include motivation [17], personality [18–21], self-discipline [22, 23], achievement goals [24], commitment [25], and psychosocial factors [26, 27]. Conative variables are regarded as highly important in 'intellectually demanding and time-intensive disciplines' [25, p. 331]. It has even been suggested that in some cases, non-cognitive constructs may be stronger predictors of academic success than admission tests [28–30]. This study is concerned with cognitive predictors, namely high school exam scores.

1.1 The special case of engineering studies

The profile of engineering students differs strongly from that of students in other disciplines. According to the graduate attributes defined by a number of engineering accreditation boards, an engineer must be able to: apply knowledge of mathematics, physics, and life sciences in order to understand, formulate, and solve engineering problems; design and conduct experiments; analyze and interpret data; develop designs that meet specified requirements; design solutions to new problems, possibly involving other disciplines; perform in multidisciplinary teams; understand engineers' responsibilities, as well as the ethical social, economic, environmental, and political impact of the engineer profession [31–34]. What differentiates engineering from other disciplines is thus its strong focus on mathematics and physics, combined with a range of domain-specific abilities and knowledge. Indeed, evidence suggests that there is a strong correlation between academic success in engineering and mathematical [35–39] and spatial abilities [40–42]. According to Zhang et al. [43], who measured demographic and

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academic performance variables in a large sample of undergraduates in engineering, science, and non-science programs at nine universities over a 13-year time period, engineering students had higher SAT-math scores than the other two groups. Similarly, a recent study [44] of about 44,000 students found that engineering students had higher SAT-math scores than the overall student average. Gender differences in engineering education have also been associated with the special nature of engineering: A variety of predictors including men's mathematical and spatial abilities, and women's verbal abilities and lower self-assessment, confidence, and self-efficacy [45–50] have been used to explain women's underachievement in engineering programs—which is the highest across disciplines [51]. Choosing for mathematics and physics in high school has been also found to be a strong predictor of students' Quality Credit Average in Engineering [52].

1.1.1 The Dutch education system

In the Netherlands, students can enroll in a university program after successfully completing six years of pre-university education (VWO), or after one year in Higher Professional Education (HBO). Foreign students are also accepted. In the fourth year of VWO, students have to choose one of the following course profiles: Culture and Society, Economy and Society, Nature and Health, and Nature and Technology. In order to complete VWO, students have to pass a school exam per course consisting of a number of tests and/or practical assignments spread over the last three years, and a national exam at the end of the last year. The final score for each course is calculated either as the average of the school exam and the national exam or as the school exam for courses not involving a national exam. The graduation diploma includes at least nine exam scores.

With a focus on the natural sciences and mathematics, Nature and Technology is the course profile that is chosen by most VWO students who later enroll in B.Sc. engineering programs. Three percent of girls and 21% of boys select the Nature and Technology profile [53]. Students with a VWO Nature and Technology diploma are admissible in any engineering program. Students with a different VWO course profile are required to have succeeded in a number of specific courses, including mathematics, physics, and for some B.Sc. programs, chemistry. Similar additional requirements apply for students enrolled after one year at HBO. Admission requirements for foreign students vary per country of origin.

Dutch universities follow the international Bachelor/Master system as part of the implementation of the Bologna Agreement. No formal restrictions are currently applied regarding the duration of a student's university study, either at B.Sc. or M.Sc. level. For a comparison between the Dutch and the American education systems, see [54].

1.2 Aim

In the field of engineering, little is known about the relationship between high school exam scores and academic performance. This study investigated the extent to which high school exam scores predict first-year grade point averages (GPA) and completion of Bachelor of Science (B.Sc.) programs at a Dutch technical university, and how these predictors vary between engineering programs. We hypothesized that of the high school exam scores, those for mathematics and physics would be the strongest predictors of academic performance in engineering.

2. Method

We collected admissions data and academic scores for all students who enrolled in a B.Sc. program at our technical university in 2003. These B.Sc. programs were: Aerospace Engineering; Applied Earth Sciences; Applied Mathematics; Applied Physics; Architecture; Chemical Engineering & BioChemical Engineering; Civil Engineering; Computer Science; Electrical Engineering; Industrial Design Engineering; Life Science and Technology; Marine Technology; Mechanical Engineering; and Systems Engineering, Policy Analysis & Management. Note that although some of these programs (e.g., Applied Mathematics and Applied Physics) may be considered as programs with a focus on applied sciences rather than engineering programs, students successfully completing any of these programs obtain a B.Sc. degree in engineering. The total number of students in this cohort was 1958, 80.6% of whom were male. The mean age was 19.63 years (SD = 2.60). Of these, 1748 students started their B.Sc. program on September 1, 2003 and obtained at least one exam score in their first year. The remaining 210 students (mean age = 21.41, SD = 4.63) were eliminated from further analysis. Comparing these 210 students with the 1748 students included in the analysis revealed that a relatively high proportion of the former enrolled via old-style VWO[1] (14% vs. 5%), Higher Technical School (12% vs. 6%), and Higher Professional Education (13% vs. 3%). The excluded students had particularly low high school

[1] In the so-called "old-style" VWO system, students sat exams for a minimum of seven courses and there were no course profiles. The last regular exam for old-style VWO took place in 2001.

exam scores in mathematics (M = 6.23, n = 90 vs. M = 6.75, n = 1,291) and sociology (M = 6.81, n = 94 vs. M = 7.21, n = 1330). Note that in the Netherlands, course grades range on a scale from 1 to 10. A grade higher than 5.5 is generally required to pass a course. For more information about the Dutch education system.

The following two variables were used as measures of academic performance.

1. GPA 1Y: first-year GPA, defined as the average of the highest scores per course obtained between September 1, 2003 and September 31, 2004.
2. B.Sc. 6.5Y: obtaining a B.Sc. diploma prior to the completion of this analysis (i.e., before July 2, 2010; six-and-a-half years after enrollment). This variable was coded as 0 = no B.Sc. diploma (yet), 1 = B.Sc. diploma, and 2 = B.Sc. diploma with honors (*cum laude*). Note that the nominal B.Sc. period is three years.

The first criterion is a measure of performance during the first year and the second is a measure of completion. We used the students' high school exam scores as predictors. Only the 12 courses for which more than 50% of the students had exam scores were included in the analysis.

First, factor analysis (principal axis factoring, oblimin rotation, Bartlett factor scores) was conducted on the high school exam scores. Next, for both academic performance criteria, the predictive value of the extracted factors, as well as that of gender, was investigated by means of stepwise linear regression analysis. Because the distribution of the B.Sc. 6.5Y variable may violate the assumptions of a linear regression analysis, a stepwise binary logistic regression analysis was used as a verification, with B.Sc. completion as a dependent variable (0 = no B.Sc. diploma, 1 = B.Sc. diploma). Finally, the relationship between the scores for the strongest factor and the two performance criteria was examined for each B.Sc. program.

This research was conducted according to the code of conduct for use of personal data by the Association of Universities in the Netherlands (VSNU) [55], which translates the Dutch Data Protection Act to the academic practice. The study was approved by the vice-rector and Director of Education of our faculty and was determined exempt from review by the Human Research Ethics Committee of the Delft University of Technology, as being a retrospective database analysis without personal identifiers.

3. Results

The distribution of students according to their prior education is shown in Table 1. Most students were admitted on the basis of a VWO diploma. The great majority of students with a Nature and Technology course profile were male (87%), whereas the Nature and Health profile comprised fewer males (58%). Students entering university with a Nature and Technology course profile (alone or in combination with Nature and Health) obtained a higher first-year GPA and were more likely to complete the B.Sc. program than those with a Nature and Health profile. Those who enrolled in the university via old-style VWO, Higher Technical Schools, or Higher Professional Education had low first-year GPA and B.Sc. completion rates compared with those students who enrolled with a Nature and Technology course profile.

We then narrowed down the analysis to focus solely on those students who had completed their secondary education in line with regulations of the new-style VWO, and who had a Nature and Technology course profile (alone or in combination with Nature and Health; n = 1050, 85.6% male students, mean age = 18.69; SD = 0.66). The other groups (other VWO course profiles, old-style VWO, foreign

Table 1. Distribution of students according to prior education (n = 1748)

		Men	GPA 1Y		B.Sc. 6.5Y	
Prior education	n	%	Mean	SD	Mean	SD
VWO (Nature and Technology & Nature and Health)	170	79	6.31	1.21	0.56	0.57
VWO (Nature and Technology)	880	87	6.29	1.23	0.61	0.54
Foreign study	139	75	6.20	1.23	0.50	0.54
VWO (other profile)	19	63	6.00	1.17	0.37	0.50
Higher Technical School (HTS)	110	84	6.01	1.55	0.10	0.30
VWO (Nature and Health)	278	58	5.87	1.38	0.53	0.52
Higher Professional Education (HBO)	53	89	5.72	1.55	0.32	0.47
VWO (old style)	96	82	5.59	1.60	0.28	0.47
University (WO)	3	67	5.27	1.97	0.00	0.00

Note. Gradient background visualizes first-year grade point averages (GPA 1Y) and B.Sc. completion rates (B.Sc. 6.5Y) from low (light) to high (dark).

Table 2. Percentages of men and women with high school exam scores, score means per course, and relationship between course scores and academic criteria (n = 1050)

High school course	% Men with exam score	% Women with exam score	Men Mean	Women Mean	GPA 1Y Correlation	B.Sc. 6.5Y Correlation
1 Physics	100	99	7.06	7.09	0.53	0.38
2 Mathematics	99	100	6.80	7.22*	0.50	0.38
3 Chemistry	99	97	6.94	7.17*	0.46	0.32
4 Sociology	98	100	7.17	7.53*	0.33	0.25
5 History	94	98	7.09	7.30*	0.24	0.22
6 General natural sciences	98	100	7.33	7.70*	0.32	0.24
7 Literature	99	99	6.80	7.34*	0.30	0.29
8 Culture and arts	69	64	6.54	6.99*	0.14	0.13
9 French	97	91	6.79	7.15*	0.29	0.23
10 German	98	99	6.78	7.13*	0.23	0.20
11 English	99	100	6.95	7.01	0.16	0.11
12 Dutch	100	100	6.65	7.11*	0.28	0.24

Note. *$p < 0.05$ for the difference between men and women calculated with a t-test. GPA 1Y: first-year grade point averages; B.Sc. 6.5Y: B.Sc. completion. The formal names of the courses in Dutch are: 1. Natuurkunde 1,2; 2. Wiskunde B 1,2; 3. Scheikunde 1,2; 4. Maatschappijleer 1; 5. Geschiedenis 1; 6. Algemene natuurwetenschappen; 7. Letterkunde; 8. Culturele en kunstzinnige vorming 1; 9. Frans 1; 10. Duits 1; 11. Engels; 12. Nederlands. Students in Culture and arts could receive either a 'satisfactory' or a 'good', corresponding to 6 and 8, respectively. A correlation of magnitude greater than or equal to 0.07 is significant, $p < 0.05$. A correlation of magnitude greater than or equal to 0.11 is strongly significant, $p < 0.001$. Gradient background visualizes grades and correlations from low (light) to high (dark).

study, Higher Technical School, Higher Professional Education, and University) did not have comparable high school course backgrounds.

3.1 *High school exam scores as predictors of academic performance*

To cope with missing values of the exam scores, the expectation maximization algorithm was first applied to the 1050 × 12 matrix of course scores of the sample, assuming a normal distribution. Table 2 shows the zero-order correlations between high school exam scores and the academic criteria. It can be seen that mathematics, physics, and chemistry had the highest correlations with the first-year GPA and B.Sc. completion. Women entered university with significantly higher average exam scores than men in 10 out of the 12 courses in Table 2.

The correlation matrix of the exam scores revealed a positive manifold, with mathematics, physics, and chemistry being the most strongly correlated variables (Table 3). To investigate the latent structure of high school courses, factor analysis was conducted. The Scree plot suggested one factor, but three factors yielded better interpretability. The initial eigenvalues were 4.65, 1.30, and 0.99, and accounted for 39%, 11%, and 8% of the var-

Table 3. Correlation matrix among high school exam scores (n = 1050)

	1	2	3	4	5	6	7	8	9	10	11
1 Physics											
2 Mathematics	0.67										
3 Chemistry	0.68	0.62									
4 Sociology	0.34	0.27	0.33								
5 History	0.35	0.23	0.32	0.46							
6 General natural sciences	0.37	0.31	0.43	0.38	0.39						
7 Literature	0.34	0.30	0.33	0.35	0.39	0.33					
8 Culture and arts	0.14	0.09	0.14	0.25	0.19	0.26	0.26				
9 French	0.34	0.31	0.35	0.34	0.36	0.32	0.34	0.15			
10 German	0.34	0.29	0.35	0.34	0.33	0.29	0.31	0.22	0.49		
11 English	0.29	0.21	0.31	0.21	0.26	0.25	0.30	0.16	0.41	0.37	
12 Dutch	0.35	0.30	0.35	0.33	0.30	0.32	0.41	0.28	0.38	0.39	0.32

Note. A correlation of magnitude greater than or equal to 0.07 is significant, $p < 0.05$. A correlation of magnitude greater than or equal to 0.11 is strongly significant, $p < 0.001$. Gradient background visualizes correlations from low (light) to high (dark).

Table 4. Rotated factor loadings of the high school exam scores (n = 1050)

		Factor 1	Factor 2	Factor 3
1	Physics	0.05	**0.83**	−0.02
2	Mathematics	−0.08	**0.83**	0.01
3	Chemistry	0.06	**0.75**	0.04
4	Sociology	**0.66**	0.01	−0.03
5	History	**0.61**	−0.01	0.04
6	General natural sciences	**0.52**	0.16	−0.02
7	Literature	**0.44**	0.04	0.17
8	Culture and arts	**0.43**	−0.13	0.06
9	French	−0.01	0.01	**0.71**
10	German	0.05	0.00	**0.63**
11	English	−0.04	0.02	**0.59**
12	Dutch	0.26	0.05	**0.35**

Note. Factor 1: Liberal Arts, Factor 2: Natural Sciences and Mathematics, Factor 3: Languages. Factor loadings above 0.30 are boldfaced. Gradient background visualizes the size of the loadings from low (light) to high (dark).

iance, respectively. The factor scores were correlated between 0.4 and 0.5. The rotated factor loadings are shown in Table 4. Factor 1 was interpreted as Liberal Arts, Factor 2 as Natural Sciences and Mathematics, and Factor 3 as Languages. As shown in Table 5, of the three factors, Natural Sciences and Mathematics had the strongest positive correlation with first-year GPA and B.Sc. completion (0.56 and 0.40, respectively).

Next, stepwise linear regression was conducted for predicting first-year GPA and B.Sc. completion (Tables 6 and 7, respectively). The Natural Sciences and Mathematics factor score was the strongest predictor for both criteria. The prediction was stronger for the first-year GPA (B = 0.603) than for B.Sc. completion (B = 0.180). The Liberal Arts factor was a relatively weak predictor, and the Languages factor had no significant predictive value. Gender had no significant predictive value for the first-year GPA and was a weak predictor (with an advantage for women) of B.Sc. completion. A binary logistic stepwise regression for predicting B.Sc. completion (0 = No B.Sc. diploma, 1 = B.Sc. diploma) yielded the same predictors as the stepwise linear regression (Table 8).

3.2 *B.Sc. program comparisons*

Table 9 shows the number of students and percentage of males per B.Sc. program and the correlations (with 95% confidence intervals) between the Natural Sciences and Mathematics factor score and first-year GPA and B.Sc. completion for each B.Sc. program. Relatively strong correlations—that is, higher than 0.6 for first-year GPA or higher than 0.5 for B.Sc. completion—were found for the Life Science and Technology, Aerospace Engineering, Electrical Engineering, Computer Science, Systems Engineering, Policy Analysis and

Table 5. Correlation matrix of predictors and criteria (n = 1050)

	All		Men		Women						
	Mean	*SD*	Mean	*SD*	Mean	*SD*	1	2	3	4	5
1 Gender[a]	0.14	0.35	0.00	0.00	1.00	0.00					
2 Factor 1 score	0.00	1.00	−0.09	0.98	0.56	0.93	0.23				
3 Factor 2 score	0.00	1.00	−0.03	1.00	0.18	1.00	0.07	0.44			
4 Factor 3 score	0.00	1.00	−0.06	0.97	0.37	1.12	0.15	0.47	0.43		
5 GPA 1Y	6.29	1.22	6.26	1.24	6.51	1.09	0.07	0.38	0.56	0.30	
6 BSc 6.5Y[b]	0.60	0.54	0.58	0.55	0.77	0.51	0.12	0.32	0.40	0.25	0.58

Note. [a] 0 = man, 1 = woman. [b] 0 = no B.Sc. diploma (n = 445), 1 = B.Sc. diploma (n = 575), 2 = B.Sc. diploma *cum laude* (n = 30). Factor 1: Liberal Arts, Factor 2: Natural Sciences and Mathematics, Factor 3: Languages. GPA 1Y: first-year grade point averages; B.Sc. 6.5Y: B.Sc. completion. A correlation of magnitude greater than or equal to 0.07 is significant, p < 0.05. A correlation of magnitude greater than or equal to 0.11 is strongly significant, p < 0.001. Gradient background visualizes correlations from low (light) to high (dark).

Table 6. Results of stepwise linear regression analysis for predicting first-year GPA (n = 1050)

	Included	B	*SE*	*p*
Gender (0 = man, 1 = woman)	No	−0.004	0.090	0.967
Factor 1 score	Yes	0.199	0.034	0.000
Factor 2 score	Yes	0.603	0.034	0.000
Factor 3 score	No	0.012	0.036	0.750

Note. F = 270.2, p < 0.001, intercept = 6.29. The values for variables not included in the final model are the estimates that would result from adding the variable to the model. Factor 1: Liberal Arts, Factor 2: Natural Sciences and Mathematics, Factor 3: Languages.

Table 7. Results of stepwise linear regression analysis for predicting BSc completion (n = 1050)

	Included	B	*SE*	*p*
Gender (0 = man, 1 = woman)	Yes	0.096	0.044	0.031
Factor 1 score	Yes	0.087	0.017	0.000
Factor 2 score	Yes	0.180	0.017	0.000
Factor 3 score	No	0.014	0.018	0.424

Note. F = 83.1, p < 0.001, intercept = 0.495. The values for variables not included in the final model are the estimates that would result from adding the variable to the model. Factor 1: Liberal Arts, Factor 2: Natural Sciences and Mathematics, Factor 3: Languages.

Table 8. Results of binary logistic stepwise linear regression analysis for predicting BSc completion (n = 1050)

	Included	B	*SE*	Wald	*p*
Gender (0 = man, 1 = woman)	Yes	0.525	0.210	6.28	0.012
Factor 1 score	Yes	0.337	0.078	18.93	0.000
Factor 2 score	Yes	0.636	0.080	63.45	0.000
Factor 3 score	No	0.044	0.080	0.30	0.586

Note. Chi-square = 155.9, df = 3, p = .000, percentage correct classification = 67.9. The values for variables not included in the final model are the estimates that would result from adding the variable to the model. Factor 1: Liberal Arts, Factor 2: Natural Sciences and Mathematics, Factor 3: Languages.

Management, and Mechanical Engineering B.Sc. programs. The lowest correlation for first-year GPA was found for Marine Technology, and the lowest correlation for B.Sc. completion was found for Architecture and for Chemical Engineering & BioChemical Engineering.

Next, we investigated which programs attracted the most competent students in Natural Sciences and Mathematics. B.Sc. programs of which the students had a high mean Natural Sciences and Mathematics factor score were generally also the programs with a high correlation between the factor score and first-year GPA (see Fig. 1; the N-weighted correlation was 0.60, p = 0.023). In other words, the students who had performed better in Natural Sciences and Mathematics at high school gravitated towards B.Sc. programs focusing more heavily on this domain.

4. Discussion

This study investigated the extent to which high school exam scores predict first-year GPA and completion of B.Sc. engineering programs. Ours was a typical engineering cohort, consisting mostly of male students who had completed a high school course profile that focused on physics, chemistry and mathematics.

In line with the accreditation criteria presented in the introduction, our findings underline the importance of domain-specific abilities in engineering. These findings contradict previous work, which found a positive correlation of both SAT-math and SAT-verbal scores with academic performance in engineering [1, 38]. However, our results are in line with Nicholls *et al.* [37] and Kokkelenberg and Sinha [44], who found that SAT-verbal score had a low predictive value for academic achievement in engineering. Zhang *et al.* [39] even found that SAT-verbal score was negatively correlated with graduation in engineering. As Lubinski also warned:

> Verbal ability could be operating as a suppressor variable and systematically precluding through indirect selection students exceptionally talented in spatial ability but relatively unimpressive in verbal ability; that is, many of these unselected students may be truly exceptional in reasoning with forms, patterns, and shapes [42, p. 349].

By analyzing the available data for each B.Sc. program we found that students with better high school exam scores in Natural Sciences and Mathematics gravitated towards programs that focused more strongly on this domain. This was a robust finding. The highest correlations between the Natural Sciences and Mathematics factor scores and first-year GPA were found for Life Science and Technology and Aerospace Engineering, two programs with a strong focus on physics and mathematics, whereas the lowest correlation between the Natural Sciences and Mathematics factor score and B.Sc. completion was found for Architecture, a B.Sc. program with a limited number of courses related to these subjects. Note, however, that even

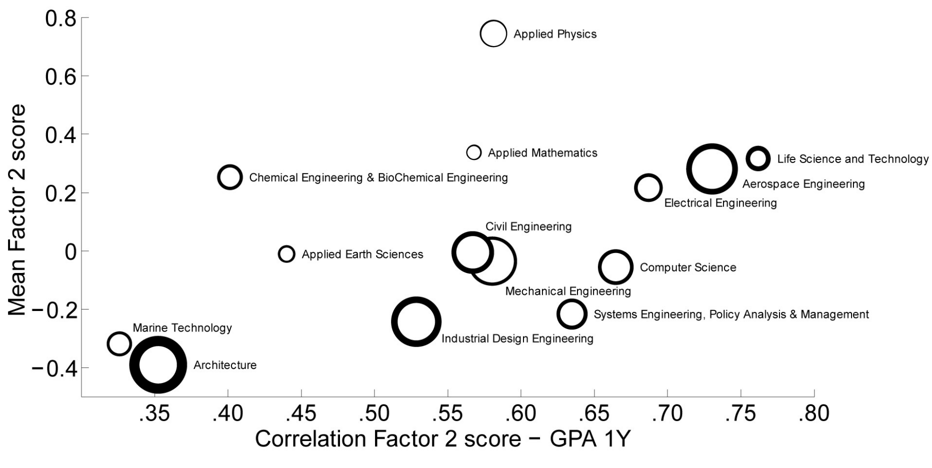

Fig. 1. Mean Factor 2 (Natural Sciences and Mathematics) score vs. correlation between Factor 2 score and students' first-year grade point averages (GPA 1Y) per B.Sc. program. The area of a circle corresponds to the sample size: The white areas represent students with a Nature and Technology course profile background (n = 1050 in total) and the total areas (black + white) represent the total B.Sc. inflow (n = 1748).

though we measured the entire cohort of students in the year 2003, the data at the level of individual B.Sc. programs may have been affected by sampling error, as only a few students were enrolled in some programs (see confidence intervals in Table 9). This may be the case for Marine Technology for example, which exhibited a relatively low correlation between the Natural Sciences and Mathematics factor score and the first-year GPA, despite being a B.Sc. program that includes course clusters of mathematics and applied physics in the first year.

In our study, gender differences were already evident during initial enrollment, with women entering university with significantly higher average exam scores than men. Gender was predictive of B.Sc. completion but not of first-year GPA. This is in line with Felder *et al.* [49], who found that while women entered engineering with higher scores than men, this advantage disappeared during the first year of study. In our study, women retained their advantage as far as B.Sc. completion was concerned. This contradicts the results Felder *et al.*, in which men were found to be more persistent. Strenta *et al.* [56] found that the attrition of women was higher than that of men in natural sciences and engineering in highly selective institutions, although to a large extent these differences could be accounted for by the scores earned in science courses during the first two years of study. These authors further discussed the chilly climate hypothesis, and over-competitiveness in particular, as a possible reason for the attrition of women. It is beyond the scope of our study to investigate the causes of gender differences in engineering. Both cognitive and non-cognitive variables are probably needed in order to explain the longitudinal academic performance of men and women in engineering [25, 57].

We found an overall correlation of 0.56 between exam scores in Natural Sciences and Mathematics and first-year GPA (Table 1). Even higher values were reached for several of the individual B.Sc. programs (Fig. 1). These are high correlations compared with predictive correlations in past research on similar topics. In the study of Ramist *et al.* [58], for example, including more than 46 000 students, SAT scores were found to predict first-year college GPA with an overall correlation of 0.36. Only after applying corrections for range restriction and measurement error did the correlation increase to 0.65. We did not apply any artifact corrections in this study, although measurement error and range restriction in particular almost certainly occurred, as engineering students represent a narrow selection from the entire population.

One of the strengths of this study is that we did not rely on self-reported high school exam scores, which have been shown to be frequently overestimated [59]; instead, we retrieved the scores from university records. A limitation of the current study is that it focused solely on high school exam scores, whereas it is likely that performance in engineering education also relates to a large number of other specific cognitive and non-cognitive abilities. A multiple regression of a range of variables is needed in order to identify which factors collectively provide the best prediction capability. It is not known whether the exam scores would even remain in the final set of predictors. Faculty practices, activities, and policies may also need to be

Table 9. Number of students and percentage of men per B.Sc. program for students with a Nature and Technology course profile (n = 1050 in total), and for the total B.Sc. inflow in parentheses (n = 1748 in total). Further shown are the correlations (95% confidence interval between parentheses) between Natural Sciences and Mathematics factor score and first-year GPA and B.Sc. completion for the students with a Nature and Technology course profile (n = 1050)

	n	% Men	GPA 1Y	B.Sc. 6.5Y
Life Science and Technology	24 (58)	67 (78)	0.76 (0.52, 0.89)	0.62 (0.29, 0.82)
Aerospace Engineering	152 (242)	93 (83)	0.73 (0.65, 0.80)	0.54 (0.42, 0.65)
Electrical Engineering	46 (74)	98 (88)	0.69 (0.50, 0.81)	0.48 (0.22, 0.68)
Computer Science	76 (117)	96 (88)	0.66 (0.52, 0.77)	0.55 (0.37, 0.69)
Systems Engineering, Policy Analysis & Management	52 (88)	87 (85)	0.63 (0.44, 0.77)	0.29 (0.02, 0.52)
Mechanical Engineering	172 (223)	97 (84)	0.58 (0.47, 0.67)	0.51 (0.39, 0.61)
Applied Physics	57 (68)	95 (78)	0.58 (0.38, 0.73)	0.49 (0.26, 0.67)
Applied Mathematics	16 (21)	87 (81)	0.57 (0.10, 0.83)	0.50 (0.00, 0.80)
Civil Engineering	101 (166)	85 (83)	0.57 (0.42, 0.69)	0.45 (0.28, 0.59)
Industrial Design Engineering	132 (236)	64 (73)	0.53 (0.39, 0.64)	0.31 (0.15, 0.46)
Applied Earth Sciences	17 (28)	76 (86)	0.44 (−0.05, 0.76)	0.48 (0.00, 0.78)
Chemical Engineering & Biochemical Engineering	36 (61)	78 (85)	0.40 (0.08, 0.64)	0.09 (−0.25, 0.40)
Architecture	132 (308)	76 (74)	0.35 (0.19, 0.49)	0.09 (−0.08, 0.26)
Marine Technology	37 (58)	89 (86)	0.33 (0.00, 0.59)	0.43 (0.12, 0.66)

Note. Gradient background visualizes correlations from low (light) to high (dark).

taken into consideration as predictors [60]. Moreover, our sole criterion was academic performance, which does not necessarily imply future professional success in engineering. Nevertheless, as long as high school exam scores are (or are intended to be) used as a predictor of academic success in engineering, domain-specific abilities as expressed by performance in Natural Sciences and Mathematics are potentially a more useful predictor than exam scores in Liberal Arts or Languages.

5. Conclusions and recommendations

This study showed that after high school courses were clustered into three factors, the Natural Sciences and Mathematics factor was the strongest predictor of first-year GPA and B.Sc. completion, the Liberal Arts factor was a weak but significant predictor, and the Languages factor had no predictive value. Differences were identified across the B.Sc. programs, with programs that relied strongly on Natural Sciences and Mathematics enrolling better-performing students.

In the Netherlands, there is an ongoing debate on introducing selection at the gate in the universities. If admission criteria are to be applied, we recommend selecting engineering students not based on the grand average of all high school exam scores or on an average that includes both verbal and mathematical abilities. Instead, a focus on domain-specific abilities as expressed by performance in physics, chemistry, and mathematics would probably be a more useful predictor of academic performance in engineering.

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Joost de Winter is assistant professor at the Department of BioMechanical Engineering, Delft University of Technology, The Netherlands. He received his Ph.D. in mechanical engineering at Delft University of Technology in 2009. His research interests include human–machine interaction, learning and individual differences, and multivariate statistics.

Dimitra Dodou is assistant professor at the Department of BioMechanical Engineering, Delft University of Technology, The Netherlands. She received her Ph.D. in biomechanical engineering at Delft University of Technology in 2006.