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Cognitive skills, personality traits and dropout in Dutch vocational education

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Abstract

Designing effective educational programs to reduce dropout in higher and vocational education requires thorough understanding of the underlying mechanisms of study success. This study examines if first-year dropout is associated with cognitive ability and personality traits as measured by a formative entry test just before enrollment in Dutch vocational education. The results show that the formative entry test outcomes do not properly identify students at risk, the association between first-year dropout and, respectively, cognitive skills and personality traits is generally not significant. Consequently, and of importance for both students and vocational education institutes, students cannot be properly informed about whether their skills and personality traits match the required skills and personality traits of the program.

Keywords: Study success, Cognitive skills, Personality traits, Vocational education

Introduction

Even though there is strong evidence that schooling outcomes (e.g. dropout, degree, grades) are associated with cognitive skills and personality traits, these relationships have hardly been examined for vocational education (Cawley et al. 2001; Heckman et al. 2006; Richardson and Norgate 2015; and references therein). This is somewhat surprising given that Dutch vocational training programs tend to have high drop-out rates and low study success (Dutch Inspection of Education 2015). Moreover, Eichhorst et al. (2015) showed in their review that low-ability youths and those working in low-skill jobs particularly benefit from vocational study completion, in that graduation fosters the transition to a more profitable employment and wage and employment outcomes in general.

Many studies have looked at the main drivers of study success. Heckman and Kautz (2012) mention that dropout and study success are simultaneously influenced by cognitive and personality drivers and Borghans et al. (2006) indicate that the relationship between personality traits and cognitive skills can exist for two reasons. First, a positive attitude towards work and performance might cause people to do their best at tests (irrespective of the rewards offered) and therefore might partly makes that cognitive skill outcomes are upward biased. Second, people might have an attitude to put effort in a task only when there are sufficient rewards but also have favorable behavioral or

labor-market outcomes. This could serve as an explanation for people with a lower cognitive test score but still a successful career.

This study contributes to the current empirical literature through a better understanding of the drivers of first-year drop out in vocational education using entry-test data that provides an accurate reflection of the cognitive skills and personality traits of students when enrolling in the vocational training program. The simultaneous measure of personality traits and cognitive ability allows us to examine if and to what extent cognition and personality are substitutes or separate-sphere drivers of first-year dropout. Moreover, the focus on vocational education is interesting as there is much more cognitive and personality diversity between the vocational training programs as there is between higher education programs. Vocational programs rely on cognition to different degrees (identified in the Netherlands through four cognitive levels), and also rely to different degrees on personality skills. We therefore also investigated whether cognitive skills and personality traits drive dropout to different degrees at different levels and different kinds of vocational education.

Tests that measure cognition have been developed and refined over the past century. Many psychologists use IQ, achievement tests, and grades (grade-point average, *GPA*) to measure “cognitive ability” or “intelligence,” and this practice is also wide-spread in economics (Heckman and Kautz 2012). Often grades are used to describe academic performance and cognitive ability [e.g. (Mitrofanu and Iona 2013)]. Research has generally supported the value of prior grades as predictors of study success, however, grades do not give insight in the underlying drivers that explain why a student is successful. Also several studies [e.g. (Noonan et al. 2005)] stated that the non-cognitive skills or personality traits should be taken into account.

Indeed, personality traits (often included under the broader banner non-cognitive skills) have strong effects on educational attainment and predict later-life outcomes with the same, or greater, strength as measures of cognition (Kautz et al. 2014). Several researchers found that personality (based on the Big Five) can be an important predictor of study success in higher education (Busato et al. 1999; Feltzer and Rickli 2009; Hakimi et al. 2011). The empirical literature indicated that conscientiousness and openness are correlated with future study success (Furnham et al. 2003), while agreeableness and neuroticism are not (Busato et al. 1999; O'Connor and Paunonen 2007). Extraversion is a factor that shows both positive and negative correlations with study success. Several variables such as age, level of education, family background and type of assessment seem to influence the nature of this correlation [e.g. (Furnham et al. 2003; Lundberg 2013; Poropat 2009)].

Even though previous studies have focused either on the relationship between study success and cognitive ability (Kappe 2011; Melse et al. 2012) or on the relationship between study success and personality traits (Feltzer and Rickli 2009; Furnham et al. 2003; Hakimi et al. 2011; Heckman et al. 2006), few studies have examined how study success is influenced by both factors (Kautz et al. 2014). To the best of our knowledge, there has even been no study that related study success to measures of personality traits and cognitive ability of which the data was collected just before educational enrollment.

Since 2012, Dutch vocational institutes organize an intake procedure, during which students take a formative entry test in which their cognitive skills are measured, together

with the Big Five personality traits (AMN 2017). The formative entry test is referred to as the *AMN* test, which stands for Assess, Manage and Navigate. This points to the formative and guiding character it is supposed to have once students are enrolled in the educational program. The objective of the formative entry test was, first of all, to give students information about the match between the own and required skills of the vocational program and about what skills should be further developed to increase study success once being enrolled in the program. Secondly, this entry test gives educational institutes insights in the current cognitive and personality state at the moment of enrollment such that students at risk can be identified at an early stage and study counselling and guidance can be more effectively targeted.

The *AMN* test is administered to incoming students at about 60% of all Dutch vocational institutes. Important for this study is that it was not mandatory for vocational institutes to include this test in the intake procedure, but if institutes decided to do so students were required to take the test. Here, we use data from this entry test to study how first-year dropout in Dutch vocational education is related to cognitive skills and personality traits. Educational institutes are not allowed to select students based on this test. Students are allowed to subscribe to several educational programs and may eventually choose one program they want to follow. This free choice can nevertheless be influenced by the test scores, but sufficient variance remains to answer our research questions.

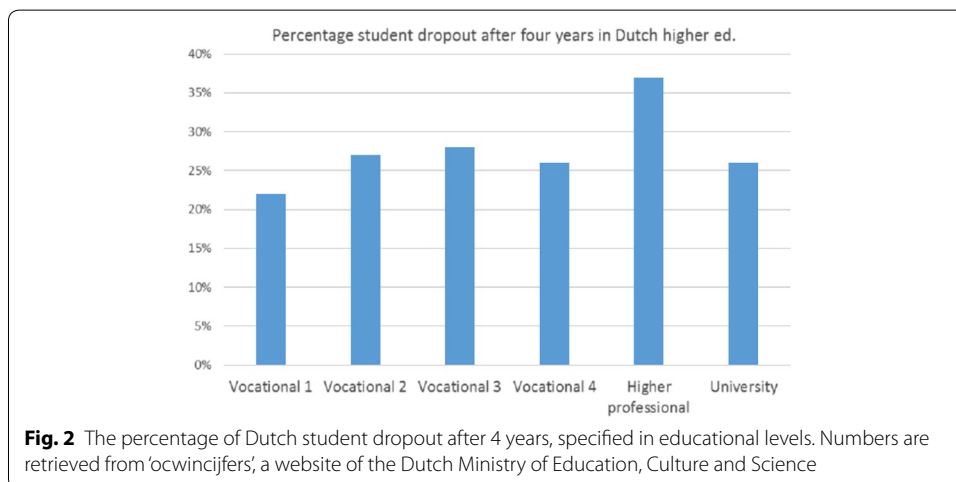
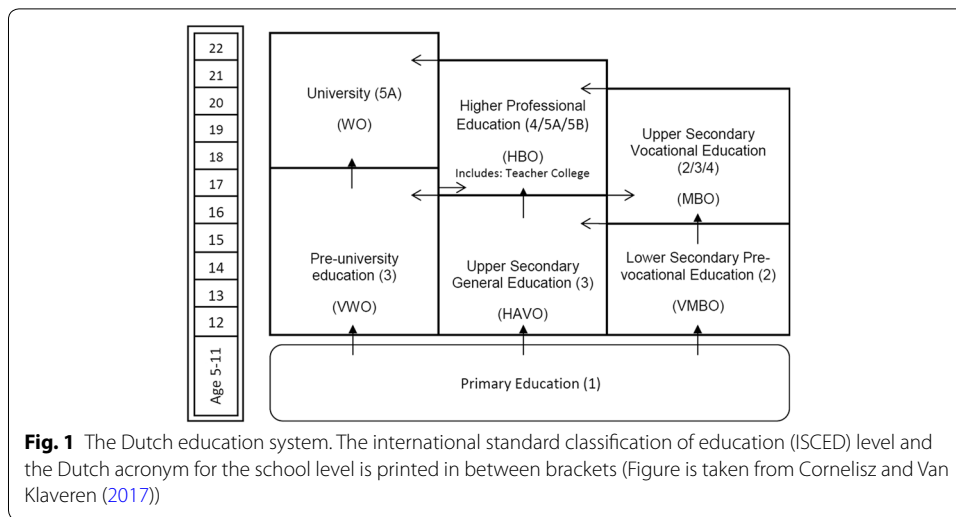
This paper proceeds as follows. “[Dutch educational system and the formative entry test](#)” section describes the Dutch education system, the formative entry test and empirical results on association between cognitive skills, personality traits and future study success. “[Data and descriptive statistics](#)” section describes the data and descriptive statistics. “[Methods and results](#)” and “[Conclusion](#)” sections present and discusses the empirical analysis and findings.

Dutch educational system and the formative entry test

The Dutch educational system

The Dutch school system (graphically illustrated in Fig. 1) tracks children into secondary education levels. In the final grade of primary education (grade six) children make a nationwide standardized test and are then tracked into three secondary education levels based upon this test and a primary school advice. About 50% of children are tracked into two pre-university or upper secondary general education, while the other 50% are assigned to the pre-vocational track (Dutch Ministry of Education Culture and Science 2013). Pre-vocational education prepares children for upper secondary education vocational education (vocational education in this paper). Vocational education is organized in large institutions and the educational programs educate students for specific professions. These programs are typically developed together with the industry in which the graduates will work after completing the program.

Vocational education has four cognitive levels, which match with the International Standard Classification of Education (ISCED) levels two, three and four. Level 2 programs are comparable with the first stage of secondary education that builds on primary education, and typically represents a more subject-oriented curriculum. Level 3 programs is comparable with the second/final stage of secondary education and provide



skills that are directly relevant to employment, usually with an increased range of subject options. Level 4 programs provides learning experiences that build on secondary education and prepare for labour market entry and/or tertiary education; the content is broader than secondary but not as complex as tertiary education.

Figure 2 shows the percentage of student dropout in the different educational tracks. The drop out is higher in higher professional education than in vocational education. Note that failure to gain qualifications at the vocational level 2 usually means that no qualification at all is attained, which can lead to a vicious cycle of unemployment, social exclusion and poverty (Cedefop 2016), whereas dropouts in other forms of higher education can usually rely on other qualifications to shield them from poverty (Dutch Ministry of Education Culture and Science 2013).

Compulsory education, degree obligation and dropout in vocational education

The Dutch compulsory schooling law requires children to go to school until the age of 18 or until pre-university, upper secondary general education or upper secondary

vocational education is successfully finished (i.e. if a degree is attained). For children enrolled in pre-university of upper secondary general education the law simply enforces that children are in education until they are 18 years old and in general these children manage to successfully finish the educational program. However, the situation is dramatically different for vocational education. Students who successfully finish pre-vocational education are, on average, 16 years old and obliged by law to continue with a vocational training program even if they do not prefer to do so. As a result of this law many children enrol in a vocational training program (level 2, 3 or 4) after successfully finishing pre-vocational education, but might drop out legitimately without a degree after 1 or 2 years when they become 18 years old. This context partly explains, at least for the Netherlands, why dropout in vocational education is relatively high.

The formative entry test AMN

Since 2012, approximately 60% of the Dutch vocational institutes require student applicants to take the formative AMN entry test during the intake procedure. The test measures a variety of cognitive skills and personality traits and the outcomes are used during an intake interview to evaluate with students the match between their own skills and required skills. For students this evaluation can be useful as it gives insights in the skills that should be further developed to be more successful once enrolled in the education program. For the institute the evaluation is useful because students who are potentially at risk (i.e. required and possessed skills differ much) can be identified at an early stage, and study counselling and guidance can be more effectively targeted. Institutes are not allowed to select students based on this test. Students are allowed to subscribe to several educational programs and institutes and may eventually choose one program they want to follow.

The process from application to enrollment is as follows. Students apply for a particular vocational program before May 1st and applicants are invited to participate in an intake procedure in the beginning of June. Importantly, applicants receive the results of the secondary school exit exams, which determines whether they are eligible to enroll in the vocational program, after the intake procedure. Conditionally on the outcomes of the exit exam and the intake procedure, students decide whether or not to enroll in the program they have applied for.

Psycho-diagnostic instruments issued in the Netherlands, like the formative entry test, are assessed by the independent Dutch Committee on Tests and Testing (COTAN, part of the National Institute of Psychologists). COTAN audits the quality of psychological tests with the objective to raise standards in the use of such tests. The formative entry test of AMN was validated by COTAN. Table 1 shows that it measures various cognitive skills and the Big Five personality traits.

The AMN cognitive skill measures are based on the Cattell–Horn–Carroll model of intelligence (Alfonso et al. 2005). This model makes a distinction between fluid and crystallized intelligence. Fluid intelligence refers to logical flexibility (called logical reasoning in AMN) and involves the ability to reason and to visualize (spatial) information. Crystallized intelligence (called learning intelligence in AMN) refers to what has been learned in the course of life and involves the knowledge gained and the understanding of the world. In total 157 items measure the different cognitive skills on a 10-points scale

Table 1 Measured cognitive skills and personality traits, with for the cognitive skills the subtest that is used to measure each skill

Cognitive skills	<i>Learning intelligence (crystallized)</i>	
	Numerical capacity	Digits (maths, reasoning)
	Verbal capacity	Words (in context)
	<i>Logical reasoning (fluid)</i>	
	Reasoning ability	Figure relations
		Word relations
		Differences
Personality traits	Evaluation ability	Differences
	Visual processing	3D-components
	Openness to experience	
	Conscientiousness	
	Extraversion	
	Agreeableness	
	Stability (complement of neuroticism)	

(the higher the score, the higher the cognitive skills). There is a separate test for level 1–2 students and for level 3–4 students. Scores are compared to a norm group of peers to distinguish the level of the student in their age group.

Personality traits are measured using the Big Five taxonomy (John and Srivastava 1999; McCrae and Costa 2008). These five personality factors are extraversion (talkative, assertive, energetic), agreeableness (good-natured, cooperative, trustful), conscientiousness (orderly, responsible, dependable), emotional stability versus neuroticism (calm, not neurotic, not easily upset) and openness to experience (intellectual, imaginative, independent-minded). Each factor of the Big Five is measured by asking applicants whether 92 statements reflecting the various factors apply to them. This is measured on a 5-point scale where 1 means not applicable at all and 5 means very applicable. For the AMN, the Big Five dimensions are defined in such way that a “positive personality” (open, conscientious, extravert, stable and agreeable) conducive to success yields positive numbers (this entails a rescoring of the typical Big Five neuroticism trait to a positive stability trait).

Data and descriptive statistics

Data and participants

This study uses information of 14.875 students who entered or registered in a vocational program offered by ROC TOP between 2012 until 2016. ROC TOP is a medium-sized regional vocational institute that provides sixty vocational education programs at all levels of vocational education. Not all entering students in vocational education took the formative entry test, which can be caused by differences between vocational programs and because of late registration of students. For the students sample considered we observe the following three situations: (1) a formative entry test outcome but no program enrollment, (2) program enrollment but not formative entry test outcome, and (3) both a formative entry tests outcome and program enrollment. The main focus in the analysis will be on the student group for which we observe both enrollment and the formative entry tests outcome, but differences between the three groups will be outlined to acknowledge the potential selective nature of the sample of analysis.

Descriptives

Table 2 shows that 24.1% of the students only took the formative entry test and did not enrol in a vocational education program. This can either be explained by the fact that students chose a different institution than they applied for or because it was impossible to match the entry test results to the student registration data. To examine potential selective enrollment in terms of the student's cognitive skills and personality traits, a probit analysis was conducted. The estimation results are shown in Table 3 and show only marginal differences for students who enrolled in a level 1–2 program, indicating that for these program levels there appears to be no selective enrolment. For level 3–4 programs enrollment is related to cognitive skills and extraversion, indicating that there is selective program enrollment in these characteristics. In the estimation models include a control variables which capture potential selection based on cognitive skill and personality trait variables (i.e. the inverse-mills ratio).

About 40% of the students enrolled in a vocational education program without taking the formative entry test. This group contained students who enrolled in programs or in years in which the test was not offered or, as stated above, the entry test data could not be matched to the student registration data. Finally, we observe for 36% of the students

Table 2 Number of students for whom only a formative entry test result was available, for whom only data was available about their enrollment in a vocational program of ROC TOP, and for whom both were available

	Observed			Total
	Formative entry test	Enrolled in vocational program	Formative entry test + enrolled in vocational program	
N	3592 (24.1%)	5928 (39.9%)	5355 (36%)	14,875
Female	–	59%	51.5%	55.5%
Age	–	22.9 (SD 9.3)	19.1 (SD 4.7)	21.1 (SD 7.7)
Graduated	–	46.3%	36.8%	41.8%
In school	–	15.5%	26.6%	20.8%
Dropout in first year	–	27.9%	29%	28.4%
Dropout total	–	38.1%	36.6%	37.4%

The latter group is the main focus of this study. For this group and for the group enrolled but without entry test data, graduation and dropout numbers are given. The main dependent measure was first-year dropout

Table 3 Probit regression estimates for enrolment in a vocational program

	Level 1–2	Level 3–4
Crystallized intelligence	0.029 (0.029)	0.083 (0.022)***
Fluid intelligence	0.058 (0.030)*	0.072 (0.021)***
Stability	0.061 (0.051)	–0.033 (0.038)
Extraversion	0.033 (0.056)	0.102 (0.040)***
Conscientiousness	0.000 (0.065)	0.022 (0.047)
Openness	–0.075 (0.063)	–0.051 (0.048)
Agreeableness	–0.081 (0.067)	–0.008 (0.054)
Constant	0.644 (0.215)***	0.121 (0.182)
Prob > chi ²	0.016	<0.001
N	2330	4449

Standard errors are in parenthesis. */**/** denote significance at 10/5/1 percent confidence level (two-sided)

both enrollment in vocational education (and consequently whether they drop out of the program) and the outcome of the formative entry test. For the 11.283 students who started a vocational program at ROC TOP in the observation period, 2344 students were still active in the educational program, 4223 students dropped out of the program and 4717 students received a diploma. Of the students who dropped out of the program, almost 80% did so in their first year. Since later dropout is a more ambiguous outcome in the sense that it may reflect success instead of failure (e.g., students may be employed and decide that they do not need a formal closure of their program), we decided to take first-year dropout as the dependent measure of the analyses.

Table 4 shows that the student population of ROC TOP differs from the student population of other vocational schools in the Netherlands. This is important with respect to the generalization of the empirical results of the study at hand. On average, the student population of ROC TOP has more students that come from poverty problem accumulation areas. These areas are defined by Statistics Netherlands, give an indication of the income of the area and derived from their annual regional income survey. Also a higher percentage of the students of ROC TOP have dropped out before and a lower percentage of students have a higher qualification than the minimally required qualification to start with a program.

As explained in “[The Dutch educational system](#)” section, Dutch law requires that children go to school until the age of 18 (compulsory schooling law) or until pre-university, upper secondary general education or upper secondary vocational education is successfully finished (i.e. if a degree is attained). Dropout may thus increase after reaching the age of 18. This could mean that drop out might be influenced by age and it has to be concluded as a control variable in the analyses. When plotting the proportion of dropout in the first year as a function of age (Fig. 3), it becomes apparent that the proportion of drop out in the first year increases when a student turns 18 (cut-off point).

Methods and results

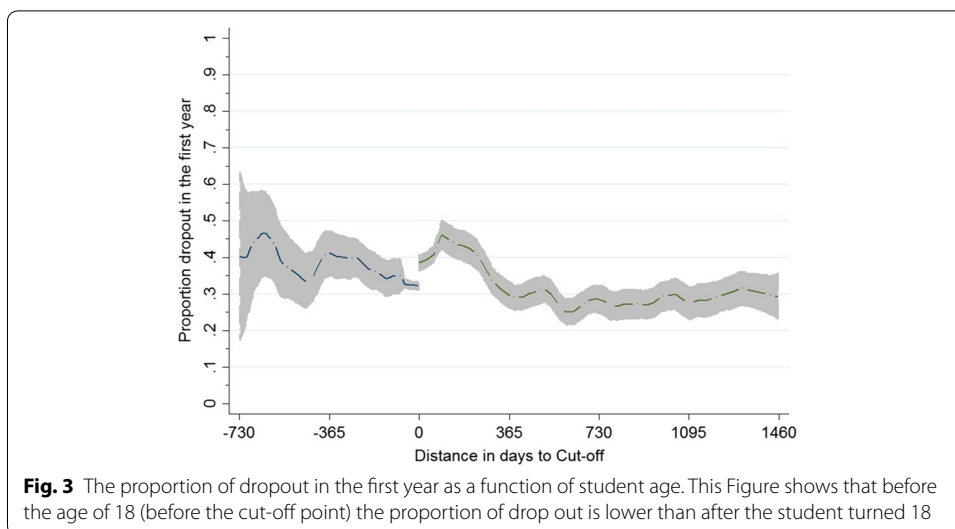
Methods

To examine the extent to which cognitive skills and personality traits can be explained by common underlying factors we first performed a principal component analysis. If cognitive skills and personality traits are independent and separate dimensions then it is expected that there are two underlying factors. Based on the outcomes of this principal component analysis variables are constructed that capture the joint variation in cognitive skills and personality traits. We note that these factors are generated by computing weighted factor scores, such that the generated variables are more efficient compared to the situation when we would simply take the average of certain constructs.

Table 4 Student population of ROC TOP, another vocational school in Amsterdam and the national Dutch average

	ROC TOP (%)	Other voc. school in Amsterdam (%)	National average (%)
Students of poverty problem accumulation areas	61	46	21
Students who dropped out of lower pre-vocational education	25.9	13.1	8.7
Students with more than the minimally required prior education	42	57	62

All numbers are retrieved from MBO scanner, website of the Ministry of Education Culture and Science, data 2016/2017



The association between first year dropout and the identified common factors underlying cognitive skills and personality traits (i.e. the constructed variables from the factor analysis) are estimated using the following model:

$$y_i = \beta_0 + \beta_1 D_{ki} + \delta' x_i + \varepsilon_i. \tag{1}$$

In this model the first-year dropout indicator of student i is represented by y_i , and D_k represents the k identified common factors underlying cognitive skills and personality traits. Matrix x_i represent the inverse Mills ratio to take account of a possible selection bias (Heckman 1979; Mills 1926), a set of student and control variables (including a program fixed effect) and ε_i represent the usual error term for which we assume that $\varepsilon_i \sim iid(0, \sigma^2)$.

By estimating Model (1) separately for the two lower and the two higher cognitive vocational tracks we can examine how differences in *required* cognitive skill-levels influence the estimated association. In other words, does the association between first-year dropout and cognitive skills depends on required cognitive skills?

In a similar fashion, we also examine how the estimated association between first-year dropout and common factors underlying personality traits depends on required personality traits by the educational program. A difficulty is that we do not observe *required* personality traits by educational program, which is why we asked six experts in vocational education to rank all educational programs offered by ROC TOP in accordance with the need of personality traits in the future occupation of the student (see Appendix B). The inter-rater reliability coefficient between the six participants was determined by estimating a two-way random-effects and the estimated coefficient turned out to be extremely high with 0.92. In order to take into account how expert opinions of required skills influence the estimated association between dropout and the identified common factors underlying cognitive skills and personality traits we estimate the following models separately for lower and higher vocational tracks:

$$y_i = \beta_0 + (\gamma_0 + \gamma_1 R_{0-25} + \gamma_2 R_{25-50} + \gamma_3 R_{50-75}) \cdot D_{PT,i} + \gamma_4 D_{CS,i} + \varepsilon_i. \tag{2}$$

In Model (2) indicator variables R refer to the personality-trait ranking of the educational program and subscript 0–25 refers to the first quartile, 25–50 to the second

quartile and 50–75 to the third quartile. Variable D_{PT} (D_{CS}) represents to the underlying common factors that can be associated with personality traits (cognitive skills). The interpretation of the gamma parameters are of huge importance in this model. Parameter γ_0 represents the association between y and D_{PT} for educational programs that are ranked by the experts as educational programs which required students with the highest personality trait-levels. The other gamma-parameters indicate how differently ranked studies *deviate* from this baseline effect. By this we mean that the association between y and D_{PT} for studies ranked in the lowest quartile is estimated to be $\gamma_0 + \gamma_1$. If the parameter estimate γ_1 turns out to be negative, it implies that the coefficient for the R_{0-25} -studies is lower than the estimated coefficient for R_{75-100} -studies (with γ_1).

Results

Principal component analysis

A principal component analysis was conducted (with varimax rotation) to examine the extent to which there is simultaneous variation in cognitive skills and personality traits. Table 5 shows the outcomes of the principal component analysis; the two columns indicate that 48% observed variation in cognitive skills and personality traits can be explained by the two factors with an eigenvalue above the cutoff of 1.0 ($\chi^2(55) = 1.1 * 10^4$ $p < 0.001$; Cronbach's alpha personality traits 0.75, Cronbach's alpha cognitive skills 0.74). Factor 1 explains underlying variation in personality traits and Factor 2 explains variation in cognitive skills.

Table 6 additionally shows the correlation matrix, such that it becomes more apparent how the various measured skills and traits are interrelated. The correlation matrix confirms that the significant correlations cluster in two groups, which is of course what the principal component analysis indicates.

Importantly, the high correlation between the cognitive skill variables on the one hand and the personality trait variables on the other indicate that causal interpretation of

Table 5 Estimation results of factor analysis

	Factor 1	Factor 2
	Cognitive skills	Personality traits
Cognitive skills		
Digits	<i>0.44</i>	0.11
Words	<i>0.64</i>	0.01
Figures	<i>0.72</i>	−0.04
Word relations	<i>0.73</i>	0.00
Differences	<i>0.68</i>	0.05
3D-components	<i>0.78</i>	0.08
Personality traits		
Stability	0.14	<i>0.57</i>
Extraversion	0.12	<i>0.73</i>
Agreeableness	0.05	<i>0.74</i>
Conscientiousness	−0.10	<i>0.74</i>
Openness	−0.01	<i>0.76</i>
Eigenvalue	2.94	2.39
% of variance	26.70	21.70

Italic numbers show in which factor the variable fits best

Table 6 Correlation matrix

	Digits	Words	Figures	Word relations	Differences	3D components	Stability	Extraversion	Agreeableness	Conscientiousness	Openness
Digits	1.00										
Words	0.24*	1.00									
Figures	0.22*	0.30*	1.00								
Word relations	0.19*	0.50*	0.45*	1.00							
Differences	0.30*	0.23*	0.38*	0.31*	1.00						
3D components	0.24*	0.31*	0.50*	0.43*	0.53*	1.00					
Stability	0.12*	0.07*	0.07*	0.08*	0.09*	0.11*	1.00				
Extraversion	0.10*	0.15*	0.02	0.09*	0.08*	0.10*	0.40*	1.00			
Agreeableness	0.01	0.04*	0.01	0.06*	0.00	0.08*	0.17*	0.39*	1.00		
Conscientiousness	-0.01	-0.09*	-0.05*	-0.03	-0.03	-0.02	0.42*	0.32*	0.42*	1.00	
Openness	0.01	0.01	-0.01*	0.01	-0.01	0.06*	0.18*	0.44*	0.55*	0.41*	1.00

*Correlation is significant at the 0.05 level

the individual cognitive skills and personality traits in relation to first-year dropout is not possible. If we would find, for example a significant relationship between 3D-components and first-year dropout then this association also captures the effect of *differences*. As a result we would for example not be able to state that first-year dropout can be improved by structurally improving 3D-components as this may not be the causal relationship observed. However, based on Tables 5 and 6, we can conclude that Personality Traits and Cognitive Skills describe rather independent variation. Because the literature uses a categorization in which the two cognitive domains (crystallized and fluid intelligence) and the Big Five personality traits are considered separately (Rammstedt et al. 2018) we follow this categorization. By examining the relationship between first-year dropout and these separately considered cognitive and personality constructs we can examine how personality traits and cognitive skills *generally* influence are associated with first-year dropout.

Regression estimates

Tables 7 and 8 show the estimation results separately for level 1–2 and level 3–4 studies. We start departure from a model with only the cognitive and personality factors and a constant included in the model (the baseline model) and then include first the inverse mills ratio to control for selective enrollment, secondly student characteristics, and finally vocational program fixed effects. The student characteristics included in the model are age and gender. The chosen stepwise approach shows how the estimation parameters of interest change when controlling for these background characteristics, which gives information on whether the identified factors are independent from these characteristics and increases precision. We note that all factor variables are standardized such that the coefficients represent association measured in standard deviations.

The results are shown separately for low and high vocational levels, as these vocational levels have distinct formative entry tests. Because of this separate representation these baseline results immediately are informative for whether *required* cognitive skills

Table 7 Baseline estimation results future dropout in the first year for level 1–2 vocational programs

	(1)	(2)	(3)	(4)
Crystallized intelligence	0.008 (0.011)	−0.013 (0.011)	−0.023 (0.012)*	−0.023 (0.013)*
Fluid intelligence	0.039 (0.012)***	0.000 (0.015)	−0.004 (0.015)	−0.011 (0.015)
Stability	0.007 (0.021)	−0.019 (0.021)	−0.038 (0.022)*	−0.040 (0.022)*
Extraversion	0.003 (0.022)	−0.015 (0.023)	−0.007 (0.023)	−0.011 (0.023)
Conscientiousness	−0.028 (0.026)	−0.027 (0.026)	−0.017 (0.026)	−0.024 (0.026)
Openness	0.008 (0.024)	0.043 (0.026)*	−0.030 (0.026)	0.048 (0.027)*
Agreeableness	0.042 (0.026)	0.083 (0.028)***	0.083 (0.028)***	0.057 (0.028)**
Enrollment prob.		−0.929(0.208)***	−0.834 (0.209)***	−0.738 (0.025)***
Constant	0.165 (0.081)**	0.573 (0.122)***	0.505 (0.123)***	0.441 (0.352)
Student controls			✓	✓
Study fixed effect				✓
R ²	0.015	0.026	0.034	0.059
N	1767	1767	1767	1767

Standard errors are in parenthesis. */**/*** denote significance at 10/5/1 percent confidence level (two-sided). Study fixed effect are enrollment year and a program dummy

Table 8 Baseline estimation results future dropout in the first year for level 3–4 vocational programs

	(1)	(2)	(3)	(4)
Crystallized intelligence	−0.008 (0.011)	−0.034 (0.024)	−0.045 (0.023)*	−0.033 (0.023)
Fluid intelligence	−0.002 (0.011)	−0.025 (0.022)	−0.017 (0.021)	−0.007 (0.022)
Stability	0.029 (0.018)	0.039 (0.020)**	0.024 (0.020)	0.028 (0.020)
Extraversion	0.014 (0.019)	−0.016 (0.032)	−0.013 (0.031)	0.001 (0.031)
Conscientiousness	−0.040 (0.023)*	−0.048 (0.024)**	−0.049 (0.024)**	−0.049 (0.024)**
Openness	0.068 (0.024)***	0.085 (0.028)***	0.068 (0.027)**	0.047 (0.029)*
Agreeableness	−0.003 (0.027)	0.001 (0.027)	0.000 (0.027)	0.005 (0.027)
Enrollment prob.		−0.555 (0.445)	−0.579 (0.439)	−0.439 (0.436)
Constant	0.080 (0.090)	0.471 (0.327)	0.479 (0.322)	0.445 (0.331)
Student controls			✓	✓
Study fixed effect				✓
R ²	0.007	0.008	0.037	0.076
N	2373	2373	2373	2373

Standard errors are in parenthesis. */**/*** denote significance at 10/5/1 percent confidence level (two-sided). Study fixed effect are enrollment year and a program dummy

influence the estimated association between dropout and the identified common factors. We expected for students enrolled in a level 1–2 program that cognitive skills and personality traits are relatively less important because students are trained for action-oriented occupations (such as supporting administrative professions or private security). Level three and four programs are more abstract and therefore cognitive skills and personality supposedly more important.

Table 7 shows for level 1–2 vocational studies that the constructs stability, openness and agreeableness are related to first-year dropout. The crystallized intelligence construct is also negatively and significantly related to dropout, but the estimated coefficient is small. The coefficient of the inverse Mills ratio variable, obtained from the probit

equation, is statistically significant thereby supporting the relationship between dropout and selective enrollment. These estimation results reveal that first-year dropout for studies which require relatively low cognitive skills is not associated with the observed variation in personality traits and cognitive skills.

Table 8 shows for level 3–4 vocational studies that cognitive skills are not related to first-year dropout, but two personality traits are. The negative sign of the conscientiousness estimate suggest that higher levels of conscientiousness is associated with lower dropout, which is consistent with the currently existing empirical evidence. Because the Big Five constructs are highly correlated we cannot make any causal claims on the effects of conscientiousness on first-year dropout.

Personality traits in different vocational programs

The estimation results of Eq. 2 in “Methods” are shown in Table 9 and indicate whether vocational studies that require more personality traits according to the six experts show stronger associations between first-year dropout and personality trait levels. We note, however, that the results should be treated with caution, as experts opinions are not a valid measure of required personality traits. The inter-rater reliability between these six participants was determined using a two-way random-effects intra-class correlation coefficient (ICC). The average ICC of 0.92 was highly reliable with a 95% confidence of [0.86, 0.96] ($F(30, 150) = 12.07, p < 0.001$). The ranking is shown in Appendix B. We note that personality trait-measures can be compared between students of all different vocational program levels. Therefore we estimate Model 2 not only separately for the different cognitive levels, but also estimate it for a pooled data in order to reduce standard errors.

Personality in this matter is a continuum and we labelled (as AMN did) one end of the continuum as positive and summed scores. A higher score does not mean more personality, but another personality. The pooled estimation results (which are most precise) indicate for study programs that require the most developed personality traits (the reference PT programs) that students whose personality traits are conducive to success tend to dropout relatively more often. The programs that fall within this category are for example nursing and social work.

Table 9 Regression estimations future dropout in the first year based on personality traits ranking

	Level 1–2	Level 3–4	Level 1–2–3–4
0–25% PT	0.051 (0.043)	– 0.005 (0.041)	0.004 (0.029)
25–50% PT	0.002 (0.038)	– 0.017 (0.033)	– 0.030 (0.025)
50–75% PT	0.039 (0.028)	– 0.032 (0.023)	– 0.009 (0.017)
Reference PT	– 0.022 (0.023)	0.030 (0.015)**	0.021 (0.012) *
Constant	0.436 (0.324)	0.350 (0.092)***	0.377 (0.074) ***
Student controls	✓	✓	✓
Study fixed effect	✓	✓	✓
R ²	0.062	0.073	0.049
N	1339	2373	3712

This ranking is divided in four quartiles. 0–25% PT refers to the first 25% of the vocational programs in this ranking (programs that require least developed personality traits), reference PT are the top 25% programs that require the most developed personality traits

Standard errors are in parenthesis. */**/** denote significance at 10/5/1 percent confidence level (two-sided). Study fixed effect are enrollment year and a program dummy

The estimated moderation effects (or interaction effects) tend to be positive, indicating that specifically those programs in which personality traits are less required students with relatively higher personality trait levels do dropout of the educational program.

Conclusion

This study empirically examined if, and to what extent, first-year dropout is associated with cognitive ability and personality traits as measured by a formative entry test just before enrollment in vocational education. The timing of the formative entry test ensures that the test outcomes gives an accurate reflection of the cognitive and personality state of the student when enrolling in the educational program, while a simultaneous consideration of personality traits and cognitive skills allows us to examine if and to what extent cognition and personality are separate-sphere drivers, in the sense that they both explain similar variation in first-year dropout. Until now, there has not been an empirical study on the potential drivers related to first-year dropout. Secondly, this study contributes by focusing on vocational education, because the examined relationship tends to be ignored for vocational education while a substantial amount of students enroll in vocational education. Thirdly, the focus on vocational education is interesting because of the diverse cognitive skills and personality traits within and between vocational tracks.

A principal component analysis suggests that personality traits and cognitive skills are independent factors. The cognitive skill constructs were highly correlated (as was already found over a century ago; Spearman 1904), as were the personality traits. The results indicate that the constructs stability, openness and agreeableness are related to first-year dropout at vocational level 1–2, and that conscientiousness and openness are related to first-year dropout at vocational level 3–4. However, it is not possible to pinpoint specifically which cognitive skill or personality trait would cause higher first-year dropout or improved study success. This means that it is not advisable to investigate the predictive value of individual cognitive skills (e.g. working memory) or individual character traits (e.g. conscientiousness) in isolation without measuring other constructs that are correlated with it.

Even with that caveat there was no robust evidence that points to a structural and significant association between the formative entry test outcomes and first-year dropout in vocational education. The inclusion of interaction effects, furthermore, did not support the claim of Heckman and Kautz (2012) that dropout is *simultaneously* influenced by cognitive skills and personality traits and that one skill/trait may reinforce the effect of another skill/trait. This indicates that the validated formative entry test is not informative with respect to how first-year dropout can be reduced.

Three possible explanations can be given for these findings. Firstly, it is possible that the entry test is not a good instrument to measure cognitive skills and personality traits that are predictive of dropout. We consider this to be an invalid argument, because the AMN is a certified and validated instrument that bears close resemblance to other cognitive and personality inventories. The cognitive subtests of the AMN closely resemble those commonly used in intelligence test batteries such as the WAIS (Wechsler 2009), while the personality questions are typical of those used in other big five-based personality inventories.

A second possible explanation is that cognitive skills and personality traits are less important for dropout in vocational education than for general secondary and higher education. This could be related to the focus on vocations that require

profession-oriented actions rather than general cognitive skills or specific personality traits. Obviously, more research is needed to validate this general conclusion.

A third explanation departs from the idea that dropout may not be a purely negative choice for many students in vocational education, reflecting failure. Students may, for example, leave education for a better alternative, notably paid employment or another possibly better fitting program. The observation that dropout is higher for students older than eighteen, for whom there is no mandatory schooling, might be substantial—i.e., the students for whom dropping out does not mean starting in a different program, but can mean dropping out of education altogether.

We note that none of these explanations excludes the possibility that test outcomes are informative with respect to other student achievement measures (i.e. study duration or variation in grades). Potentially, for example, information on personality traits and cognitive skills can help to provide students with more optimal guidance. Also, ROC TOP as a vocational institute attracts relatively poor performing students. This may result in an outflow of students who possess the appropriate level of personality traits to be successful in the program towards institutes with a higher proportion of fellow students who also possess the appropriate level of personality traits. More research is needed to investigate this explanation.

As a final note, we would like to reiterate that the formative entry test outcomes are used during an intake interview with the objective to evaluate with students the match between their own skills and required skills. For students the outcomes should give information on what skills and (if possible) personality traits should be improved in order to be successful in the educational program. For the study program the outcomes should identify students who are potentially at risk (i.e. required and possessed skills differ much) at an early stage such that study counselling and guidance can be more effectively targeted. The empirical results show that the formative entry test outcomes do not accurately identify students at risk, because the association between first-year dropout and, respectively, cognitive skills and personality traits is generally not significant. Consequently, and of huge importance for both students and vocational education institutes, students cannot be properly informed about whether their skills and personality traits match the required skills and personality traits of the program.

Abbreviations

AMN: Assess, Manage and Navigate. This test assesses cognitive and personality ability when students enrol in (vocational) education; GPA: grade point average; ICED: International Standard Classification of Education.

Authors' contributions

All authors contributed substantially to this work. All authors structured, wrote and revised the manuscript at all stages before approving this final manuscript. All authors read and approved the final manuscript.

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Competing interests

The first author works within the institution that was subject to the research.

Availability of data and materials

Please contact the first author for further details on the data set.

Ethics approval and consent to participate

We used administrative data from ROC TOP and acquired approval of this school to use this data.

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Appendix A

Table 10 importantly shows that not all students who are enrolling in a certain educational program take the formative entry test. This could potentially bias the results since we are considering a selective sample of students. We also show that the take-up increases over time, which indicates that the formative tests is relatively more frequently used in later academic years. In the empirical analysis where we evaluate how the formative entry test is associated with drop out in the first year we therefore control for the

Table 10 Distribution of students and AMN tests in parenthesis per educational program

Program	Inflow year					
	2012	2013	2014	2015	2016	Total
Social services	444 (128)	288 (113)	220 (174)	254 (172)	203 (136)	1409 (723)
Entree	221 (83)	236 (76)	331 (146)	331 (110)	158 (89)	1277 (504)
Pedagogic work	363 (45)	211 (43)	235 (134)	176 (110)	214 (151)	1199 (483)
Nurse	195 (2)	186 (15)	165 (15)	162 (52)	145 (50)	853 (134)
Sales	175 (58)	162 (68)	124 (66)	146 (92)	98 (78)	705 (362)
Private security	59 (18)	75 (12)	145 (47)	233 (159)	125 (64)	637 (300)
Sport and movement	199 (156)	136 (89)	99 (50)	84 (77)	107 (104)	625 (476)
Advice and guidance in sales	85 (27)	116 (70)	86 (56)	114 (85)	105 (92)	506 (330)
Supporting administrative professions	137 (48)	125 (60)	101 (67)	79 (64)	33 (33)	475 (285)
Medical assistant	196 (1)	144 (3)	40 (0)	48 (0)	46 (2)	474 (6)
Social care	161 (19)	116 (22)	74 (44)	47 (42)	15 (14)	413 (141)
Nurturing	84 (7)	80 (19)	83 (6)	57 (33)	78 (56)	382 (121)
Travel, leisure and hospitality	99 (88)	66 (60)	77 (76)	61 (60)	51 (51)	354 (335)
Management retail	88 (30)	87 (14)	92 (51)	53 (30)	32 (18)	352 (143)
Marketing, communication and events	87 (42)	59 (37)	71 (48)	37 (28)	70 (46)	324 (210)
Financial administrative professions	63 (29)	48 (28)	64 (39)	49 (34)	94 (51)	318 (181)
Secretarial professions	76 (31)	32 (20)	33 (12)	22 (14)	37 (22)	200 (99)
Legal-administrative professions	27 (24)	20 (18)	33 (32)	25 (25)	27 (26)	132 (125)
Social work	34 (3)	22 (8)	20 (17)	27 (26)	20 (18)	123 (72)
Facilitair management	32 (28)	28 (27)	13 (12)	23 (22)	21 (20)	117 (109)
Bike technology	29 (11)	19 (16)	15 (15)	18 (10)	24 (1)	105 (53)
Financial services	20 (19)	16 (16)	18 (17)	12 (11)	17 (16)	83 (79)
Audio visual production	42 (14)	26 (20)	0	0	0	68 (34)
Entrepreneurship retail	11	11 (5)	8 (6)	8 (6)	25 (22)	63 (39)
Application development	23 (16)	11 (8)	0	0	0	34 (24)
Hair care	16 (6)	2 (1)	0	0	0	18 (7)
Catering/bakery entrepreneur	0	0	0	0	16 (16)	16 (16)
Media design	10	0	0	0	0	10 (0)
Pharmacist's assistant	0	0	9	0	0	9 (0)
ICT support	1	0	0	0	0	1 (0)
Fastservice	0	1	0	0	0	1 (0)
Total	2977 (933)	2323 (854)	2156 (1130)	2066 (1262)	1761 (1176)	11,283 (5355)

potential bias by, first of all, including the student controls and by including program fixed-effects empirical analysis.

Appendix B

See Table 11.

Table 11 The top 31 of the educational programs, ranked by six experts in vocational education

		a	b	c	d	e	f	Total
1	Bike technology	6	4	2	1	2	9	24
2	Application development	1	10	3	5	5	1	25
3	ICT and media management	2	1	4	2	16	6	31
4	Audio visual production	4	8	1	7	12	5	37
5	Media design	5	9	12	8	3	4	41
6	Supporting administrative professions	9	5	6	6	8	8	42
7	ICT support	3	3	10	4	23	3	46
8	Legal-administrative professions	8	13	5	14	4	12	56
9	Private security	12	2	21	3	13	17	68
10	Secretarial professions	10	12	16	11	6	21	76
11	Fastservice	20	7	13	17	14	7	78
12	Financial services	11	19	14	12	10	14	80
13	Management retail	13	17	7	21	22	2	82
14	Entrepreneurship retail	15	16	15	18	9	11	84
15	Facilitair management	14	14	11	16	15	15	85
16	Financial administrative professions	7	28	8	10	19	13	85
17	Catering/bakery entrepreneur	16	15	17	19	7	16	90
18	Marketing, communication and events	18	18	22	20	1	18	97
19	Hair care	22	6	23	13	18	24	106
20	Advice and guidance in sales	17	21	29	23	11	10	111
21	Sport and movement	26	25	26	9	17	25	128
22	Social services	28	30	9	25	20	19	131
23	Pharmacist's assistant	19	26	20	15	29	23	132
24	Sales	27	20	19	22	24	20	132
25	Nurturing	25	11	28	26	26	30	146
26	Travel, leisure and hospitality	21	29	31	24	25	22	152
27	Medical assistant	23	31	18	27	28	29	156
28	Social care	29	22	24	29	30	28	162
29	Nurse	24	23	25	28	31	31	162
30	Pedagogic work	30	24	27	30	27	26	164
31	Social work	31	27	30	31	21	27	167

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References

- Alfonso VC, Flanagan DP, Radwan S (2005) The impact of the Cattell–Horn–Carroll theory on test development and interpretation of cognitive and academic abilities. In: Flanagan DP, Harrison PL (eds) *Contemporary intellectual assessment*, 2nd edn. Theories, tests and issues. The Guilford Press, New York, pp 185–202
- AMN (2017) Amn talentscan productomschrijving. Arnhem. Retrieved from <https://www.amn.nl/onderwijs/mbo/talentscan-mbo/>
- Borghans L, Meijers H, Ter Weel B (2006) The role of noncognitive skills in explaining cognitive test scores. *Learning*. <https://doi.org/10.1111/j.1467-629X.1980.tb00220.x>
- Busato VV, Prins FJ, Elshout JJ, Hamaker C (1999) The relation between learning styles, the Big Five personality traits and achievement motivation in higher education. *Personal Individ Differ* 26:129–140
- Cawley J, Heckman J, Wytlačil E (2001) Three observations on wages and measured cognitive ability. *Labour Econ* 8(4):419–442. [https://doi.org/10.1016/S0927-5371\(01\)00039-2](https://doi.org/10.1016/S0927-5371(01)00039-2)
- Cedefop (2016) Leaving education early: putting vocational education and training centre stage. Volume II: evaluating policy impact, vol II. Publications Office of the European Union, Luxembourg. <https://doi.org/10.2801/967263>
- Cornelisz I, Van Klaveren C (2017) Student engagement with computerized practicing: ability, task value and difficulty perceptions. *J Comput Assit Learn*. <https://doi.org/10.1111/jcal.12292>
- Dutch Inspection of Education (2015) De staat van het onderwijs 2013–2014
- Dutch Ministry of Education Culture and Science (2013) *Kerncijfers 2009–2013*, The Hague
- Eichhorst W, Rodríguez-Planas N, Schmidl R, Zimmermann KF (2015) A road map to vocational education and training in industrialized countries. *ILR Rev* 68(2):314–337. <https://doi.org/10.1177/0019793914564963>
- Feltzer MJ, Rickli S (2009) De Invloed van Persoonlijkheidskenmerken en Andere Factoren op Studie-Uitval in het Hoger Onderwijs. *Psychologie Schweizerische Zeitschrift Für Psychologie Und Ihre Anwendungen*
- Furnham A, Chamorro-Premuzic T, McDougall F (2003) Personality, cognitive ability, and beliefs about intelligence as predictors of academic performance. *Learn Individ Differ* 14:49–66. <https://doi.org/10.1016/j.lindif.2003.08.002>
- Hakimi S, Hejazi E, Gholamali Lavasani M (2011) The relationships between personality traits and students' academic achievement. *Procedia Soc Behav Sci* 29:836–845
- Heckman JJ (1979) Sample selection bias as a specification error. *Econometrica* 47(1):153–161
- Heckman JJ, Kautz T (2012) Hard evidence on soft skills. *Labour Econ* 19(4):451–464. <https://doi.org/10.1016/j.labeco.2012.05.014>
- Heckman JJ, Stixrud J, Urzua S (2006) The effects of cognitive and noncognitive abilities on labour market outcomes and social behaviour. *J Labor Econ* 24(3):411–482 (**NBER working paper series No. 12006**)
- John OP, Srivastava S (1999) The Big Five trait taxonomy: history, measurement, and theoretical perspectives. In: Pervin LA, John OP (eds) *Handbook of personality: theory and research*. Guilford Press, New York, pp 102–138
- Kappe R (2011) Determinants of success: a longitudinal study in higher professional education. *Vrije Universiteit, Amsterdam*. <https://doi.org/10.1017/CBO9781107415324.004>
- Kautz T, Heckman JJ, Diris R, Ter Weel B, Borghans L (2014) *Fostering and measuring skills: improving cognitive and non-cognitive skills to promote lifetime success*. OECD Publishing, Paris **10.1787/19939019**
- Lundberg S (2013) The college type: personality and educational inequality 31(3):421–441
- McCrae RR, Costa PT (2008) Empirical and theoretical status of the five-factor model of personality traits. *The SAGE handbook of personality theory and assessment*. Guilford Press, New York, pp 273–294. <https://doi.org/10.4135/9781849200462.n13>
- Melse E, Van Montfort K, Van Muijen JJ (2012) Het rendement van selectie aan de poort. *ESB Onderwijs Wetenschap* 97(4635):312–315
- Mills JP (1926) Table of the ratio: area to bounding ordinate, for any portion of normal curve. *Biometrika* 18(3/4):395–400
- Mitrofanova N, Iona A (2013) Predictors of academic performance. The relation between the Big Five factors and academic performance. *Procedia Soc Behav Sci* 78:125–129. <https://doi.org/10.1016/j.sbspro.2013.04.264>
- Noonan BM, Sedlacek WE, Veerasamy S (2005) Employing noncognitive variables in admitting and advising community college students. *Community Coll J Res Pract* 29(6):463–469. <https://doi.org/10.1080/10668920590934170>
- O'Connor MC, Paunonen SV (2007) Big Five personality predictors of post-secondary academic performance. *Personal Individ Differ* 43(5):971–990. <https://doi.org/10.1016/j.paid.2007.03.017>
- Poropat AE (2009) A meta-analysis of the five-factor model of personality and academic performance. *Psychol Bull* 135(2):322–338. <https://doi.org/10.1037/a0014996>
- Rammstedt B, Lechner C, Danner D (2018) Relationships between personality and cognitive ability: a facet-level analysis. *J Intell* 6(28):1–13. <https://doi.org/10.3390/jintelligence6020028>
- Richardson K, Norgate SH (2015) Does IQ really predict job performance? *Appl Dev Sci* 19(3):153–169. <https://doi.org/10.1080/10888691.2014.983635>
- Spearman C (1904) "General intelligence", objectively determined and measured. *Am J Psychol* 15(2):201–292
- Wechsler D (2009) *Wechsler individual achievement test*, 3rd edn. Psychological Corporation, San Antonio