Identifying Students at Risk of School Failure in Luxembourgish Secondary School

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Abstract

If teachers knew in advance whether their students are at risk of school failure, they would have the opportunity to supply these students with additional or special instruction. In Luxembourg, the likelihood of failure in school is particularly high. Taking this result into account, this paper deals with the identification of variables of primary school students that might help predict school failure in Luxembourgish secondary school. Failure was defined as (a) descending from a higher track to a lower track, (b) repeating a class, or (c) showing insufficient achievements in two main subjects. First, we chose variables from a cohort of $N = 2787$ students who finished primary school in 6th grade and started secondary school in 7th grade in school year 2008/2009 for further analyses which were shown to be effective in predicting school failure in past investigations. These variables entailed both information about students' achievements and their social background. We then examined similarities and differences in these variables between students who failed and those who succeeded. Additionally, logistic regression analyses showed that primary school achievements in mathematics and languages were the strongest predictors of failure in secondary school, followed by students' age and students' school-related behaviors. Finally, we could show that the same accuracy of prediction of school failure (mean $\kappa = .183$) was obtained when a fast and frugal algorithm, containing only three predictors or less, instead of a linear regression model was used. The findings support the hypothesis that poor academic achievement is one of the strongest predictor of school failure, and that accurate predictions can be made without using complex regression models.

Keywords: School failure, Students at risk, Secondary school, Prediction, Logistic regression, Fast-and-frugal decision tree

1. Introduction

1.1 Introduction into the problem

For teachers, knowledge about and identification of predictors of school failure is of huge importance since it would enable educational personnel to provide students being at risk of school failure with adequate instruction. In Luxembourg, the likelihood of failure in school is particularly high, as has been documented, for example, by Borodankova and de Almeida Coutinho (2011). They showed that in Luxembourg about 18 % of the students repeated a class at least once in primary school, and about 24 % repeated a class in secondary school until 9th grade. The success rate within regular schooling time is one of the lowest worldwide (Levy & Wallossek, 2012). Possible causes may be the high number of immigrants and the fact that there is not one language of instruction, but three (Landgrebe, 2006). Both the high percentage of immigrant students and multilingualism in instruction have been shown to contribute to low achievements in the PISA test (Blanke, Böhm, & Lanners, 2004).

The purpose of the present investigation was twofold. On the one hand, we attempted to identify different factors that contribute to school failure in Luxembourg. Rather than referring to diagnostic measures that have been shown to predict future school failure to some extent, but were not being implemented regularly in the classroom by teachers, we placed emphasis on information to which teachers actually have access while giving lessons. On the other hand, we sought to ascertain a model of prediction of school failure that is easily applicable by teachers without referring to a large amount of variables and complex methods of their statistical analysis. We therefore compared two models of prediction, one involving a rather large amount of information (multiple regression), the other resorting to only a fraction of information available (fast-and-frugal decision tree).

1.2 Factors that increase the risk of school failure

There is a large body of research that has identified factors contributing to school failure. However, the term school failure has been understood and operationalized differentially. The majority of studies dealing with prediction of school failure have used school dropout as criterion. Most of them are concerned with dropout in high school, that is, leaving school before doing the final examinations. Only a few studies have examined predictors of dropping out of school before students reach 12th grade or earlier (e. g., Rumberger, 1995). Other studies have focussed on predicting academic success (or failure) defined more broadly, such as passing grades throughout high school, showing reasonable scores on standardized achievement tests, or graduating from high school on time (Finn & Rock, 1997). Some researchers have classified students at risk as those who exhibit academic, behavioral, or attitudinal problems that lead to school dropout (Janosz, Le Blanc, Boulerice, & Tremblay, 2000). Despite the different measures of school failure, the factors that have been identified as predictors of school failure are alike. The concept of risk has been borrowed from the field of medicine and conveys the notion that the existence of particular conditions (or risk factors) increases the likelihood that an individual will experience negative consequences (Kraemer, Kazdin, Offord, Kessler, Jensen, & Kupfer, 1999). With regard to school outcomes, well-established risk factors come from various domains, such as the individual, family, and school (Rumberger & Lim, 2008; Wells, 1990).

Poor academic achievement, measured as grade point average or achievement test scores, is one of the most important individual predictors of school failure (Battin-Pearson, Newcomb, Abbott, Hill, Catalano, & Hawkins, 2000; Krohn, Thornberry, Collins-Hall, & Lizotte, 1995; Suh, Suh, & Houston, 2007).

Beyond academic achievement, students' classroom behaviors seem to play an important role in predicting future success or failure. If students—even when they are supposed to be at risk due to certain adverse conditions—attend school regularly, participate in extracurricular activities, or complete required work in school, they reduce the probability of school failure (Finn & Rock, 1997). However, other behaviors increase the probability of school failure, for example, absenteeism from school (Suh, et al., 2007) or drug use (Finn & Rock, 1997).

Concerning students' families, it is well documented that students who are part of an ethnic minority participate less often in learning-related class activities (Finn, Folger, & Cox, 1991), exhibit more behavior problems in school (Farkas, Grobe, Sheehan, & Shuan, 1990), and show higher rates of absenteeism from school (Velez, 1989) than their ethnic-majority peers. Moreover, low socioeconomic status of families is a frequently cited predictor of school failure. A number of studies have reported that language learning at home is affected by family income. For example, the availability of stimulating books as well the intellectual encouragement and support occur less often in poor families than in families with higher income (Hart & Risley, 1992; Ninio, 1990).

Socioeconomic factors are not only linked to the individual or family, but do also arise from the educational environment of students. There have been shown differences in classroom instruction between low-socioeconomic status and high-socioeconomic status schools. Teachers in schools with rather low socioeconomic status might provide less time that is devoted to instruction in academic skills than teachers giving lessons in school with high socioeconomic status (Cooper & Speece, 1990). Particularly in school systems with hierarchical tracking, the development of knowledge and competences has been shown to be slower for students attending lower tracks than for those attending higher tracks (Baumert & Schümer, 2001), hence yielding higher failure rates for the former than for the latter.

1.3 Methods of identifying predictors of being at risk

While linear regression techniques provide an invaluable tool for predicting certain criteria (such as school failure), they do have some disadvantages. One disadvantage is that parameter estimates of regression models are based on empirical data samples and therefore are necessarily prone to uncertainty, since the available data sample can be assumed to contain sample-specific errors (Dawes, 1979). Moreover, measurement of the data is not error free, so that parameter estimates are usually biased by small sample sizes and measurement error in the observed data. This means that linear regression weights that are optimized by using small samples in order to predict (more or less) imprecisely measured criteria may lead to models which have no more predictive validity in new samples than those created using randomly generated weights (Dawes & Corrigan, 1974).

Using linear equations to model predictions has major theoretical implications. First, the relationship between predictors and the criterion is assumed to be linear (or log-linear if the criterion is a binary variable); second, a low weight of one predictor can be compensated by a high weight of another predictor, without changing the value of the criterion; third, the criterion is always based on all predictors inserted into the regression model. None of these assumptions is necessarily true, and especially the latter two assumptions have been called into question by research dealing with judgment heuristics. When predictions are made in real life, optimally weighting a large amount of variables is not necessarily what results in the most exact prediction. Beyond a certain point, increased accuracy may have no practical usefulness, or not enough usefulness to balance any increased effort necessary to attain it.

Kahneman and Tversky have argued that people often base their predictions on simplified decision strategies instead of full, systematic analyses of the available data (Kahneman & Tversky, 1973; Tversky & Kahneman, 1974). One hypothesis about how people make predictions beyond taking all available information into account is the take-the-best heuristic, suggested by Gigerenzer and Goldstein (1996). This heuristic is an instance of so-called fast-and-frugal heuristics, which are fast in execution and frugal in the information used (Gigerenzer, 2008). It consists of a search rule, a stopping rule, and a decision rule. According to the search rule, possible predictors (Gigerenzer calls them cues) are looked up which have a high validity, that is, which predict the criterion to a fairly high degree. The stopping rule claims that as soon as a cue allows for a decision or prediction, no other cues will be considered. The process is finalized by a decision about the alternative values of the criterion according to the cues that had been looked up. The take-the-best heuristic was designed to help people to choose between two alternatives. Applied to the identification of being at risk of school failure, the alternatives between which have to be chosen are "being at risk" versus "not being at risk". The resulting classification rule can be depicted as a fast-and-frugal decision tree, allowing for a quick decision at each node of the tree (Martignon, Vitouch, Takezawa, & Forster, 2003).

The take-the-best heuristic has been applied in several studies comparing the effectiveness of simple linear models to that of heuristic models (Dhami & Harries, 2001; Dhami & Ayton, 2001; Hogarth & Karelaia, 2007, 2006; Gigerenzer, 2008; Katsikopoulos, Pachur, Machery, & Wallin, 2008) and has also been applied to predictions of high school dropout rates (Gigerenzer, Todd, & the ABC Research Group, 1999). Consistently, heuristic models outperformed regression models when the sample sizes were rather small and the regression models rather complex.

1.4 Research question and hypotheses

With this study, it was the first time that variables obtained from students attending primary school were examined with regard to their predictive validity for school failure in secondary school in Luxembourg. As a first step, we attempted to identify different variables that contribute to school failure in Luxembourg. We were solely interested in those variables that were accessible by teachers in primary school. Therefore, we abstained from the use of diagnostic instruments (such as intelligence tests, screening tests, tests to assess learning disabilities, or inventories measuring learning strategies) since they were hardly (if ever) used in Luxembourgish primary school. Furthermore, we compared two methods of predicting school failure. One method, which is used in most cases when it comes to predict school failure on the basis of variables that seem to contribute to this criterion, is linear regression analysis. The other method stems from Gigerenzer and Goldstein (1996) and is called the take-the-best heuristic. The take-the-best heuristic relies on only a few variables and offers a simple algorithm for predicting school failure. It additionally has proven to be at least equally (or even more) accurate in making predictions than linear regression models.

Concerning the *variables of prediction*, we assumed that, based on previous research, achievement variables of 6^{th} graders should be most predictive for success or failure in secondary school. Higher achievements in primary school should result in lower probabilities of failure in secondary school. Additionally, with regard to family factors we hypothesized that ethnic affiliation of the students should also significantly contribute to the prediction of school failure. In particular, we assumed that immigrant students should be more likely to fail than native students. Finally, we supposed the track students attend in secondary school to be a school-related moderator of the likelihood of school failure. We expected higher failure rates in lower school tracks, and in addition differences in the strength of the relationship between predictors and the criterion.

With respect to the *methods of prediction*, we hypothesized that the take-the-best heuristic should predict school failure with the same accuracy as (or even better than) linear regression models should do.

2. Method

2.1 Sample and variables

2.1.1 The sample

The data used in the article were drawn from a cohort of $N = 2787$ students who finished primary school in 6^{th} grade and started secondary school in 7^{th} grade in school year 2008/2009. Additionally, we had access to data of the same students over a period of three years, ending in school year 2010/2011 (which was for the most students of the cohort 9^{th} grade). The anonymized data were provided by the Luxembourgish Ministry of Education and by the

Luxembourgish school monitoring, which takes place annually.

Among the data collected, we chose 13 variables for analysis according to three criteria: (1) They were mentioned in several other empirical studies on school failure; (2) they were easily accessible by primary school teachers; (3) they were substantially correlated with respect to school failure as defined in our study. These variables represented individual (i. e., achievement variables), familial (i. e., ethnicity), and school-related (i. e., school track) characteristics (cf. Wells, 1990).

2.1.2 Dependent variable

The dependent variable of the study was failure of students in secondary school. We defined school failure if one of three criteria within the first three years of secondary school were met: (a) Students descended from a higher track to a lower track, (b) repeated a class, or (c) showed insufficient achievements in two main subjects. Concerning the third criterion, academic achievements were measured by the school marks students obtained in their third year in secondary school. Main subjects were mathematics, German, and French. We chose the third year of secondary school since after this year all students (except for those who repeated a class) were supposed to enter a new level of education in secondary school.

From all students, n = 735 (26.4 %) fulfilled the criteria of school failure.

2.1.3 Predictors obtained in 6th grade

School marks in 6th grade. We used school marks of the students obtained in 6th grade in the subjects mathematics, German, and French as predictors. School marks were given as points, ranging from 0 to 60, with points below 30 representing insufficient achievements.

Results of standardized achievement tests. Indicators of academic achievement were test scores obtained from standardized achievement tests that were administered in 6th grade. These tests comprised tasks from the curricular fields mathematics, German, and French. Test scores were standardized such that the population mean was fixed to 0, and the standard deviation was set to 1.

Judgments of school-related behaviors. The school reports of the students were supplemented with judgments of their teachers regarding school-relevant behaviors. These behaviors were measured by three scales, which were (a) engagement in school, (b) acquiescence to class and school rules, and (c) social behavior. The scales had four levels, with 1 (occurs rarely) and 4 (occurs frequently) constituting the poles of the scale. Internal consistency of all three scales was considerably high in the sample ($\alpha_{eng.}$ = .91, $\alpha_{acq.}$ = .89, $\alpha_{soc.}$ = .89).

Students' age. The age of the students was entered as a metric variable into the analyses.

Students' gender. Gender of the students was coded as 1 (male) and 0 (female).

Students' ethnicity. Ethnicity of the students was given by their nationality. We distinguished between native (i. e., Luxembourgish) students, Portuguese students, and students from other ethnicities. This distinction was made because the Portuguese students are the largest ethnic minority in Luxembourg. Students' ethnicity was coded as two binary dummy variables with students being neither Luxembourgish nor Portuguese forming the reference group. The first dummy variable represented Luxembourgish students, the second dummy variable represented Portuguese students.

2.1.4 Potential moderator variable

School track affiliation. In some European countries (such as Luxembourg, Germany, Austria, or Switzerland), secondary school is composed of hierarchical tracks. These tracks offer different curricula and different degrees. The assignment of students to these tracks depends mainly on their achievements in primary school, but research has shown that also the students' social background might affect school placement (Arnold, Bos, Richert, & Stubbe, 2007; Bos, Voss, Lankes, Schwippert, Thiel, & Valtin, 2004; Klapproth, Glock, Krolak-Schwerdt, Martin, & Böhmer, 2013). In Luxembourg, three hierarchical tracks constitute secondary school. Students are generally oriented towards the highest track when they have a flawless achievement profile. An achievement profile showing difficulties in one or more subjects generally leads to on orientation towards the middle track, while students with major learning difficulties are oriented towards the lowest track. Since only a small number of students attended the lowest track, we merged the middle and the lowest track, thus making track affiliation a binary variable, containing the levels "academic track" and "vocational track".

2.2 Data analyses

Data analyses were done in several successive steps. First, we examined similarities and differences in the predictor variables chosen for our study between students who failed and those who succeeded. Differences were examined using t-tests for independent samples.

Additionally, correlations were obtained between the predictors, the moderator variable, and the criterion. In order to test our hypotheses, logistic regression analyses were run, with “school failure” as binary criterion. Logistic regression analysis yields odds ratios as regression weights, which reflect the raise of the chances of school failure, given a one-unit increase of the predictor. Prior to regression analyses, we z-transformed all predictors in order to make comparisons of odds ratios meaningful. Thus, one unit was equal to one standard deviation of the respective predictor.

We estimated two different regression models. In Model 1, all predictors obtained from students in 6th grade were inserted, while disregarding a possible moderator effect of the track to which the students were oriented after primary school. This model was therefore strictly based on information teachers had access to in primary school. Model 2, however, took into account how the predictive power of the variables was moderated by the track the students were assigned to in secondary school. Since a moderator effect may not only be displayed by a significant odds ratio obtained from the variable “school track”, but also as an interaction between all 6th grade variables and the school track, we constructed for each predictor interaction terms additionally.

In order to estimate how well the outcome “school failure” was predicted by regression models, we compared predicted versus actual membership of the students to either the school failure group or the success group. Prediction of school failure was made by assigning each student a number, indicating the probability of school failure, on the basis of the regression weights obtained from both regression models. We chose the cut-off probability value for classifying students into both groups (failure versus success) as p = .50, that is, each individual scoring at p = .50 or above was considered being classified as member of the school-failure group. The validity of the models for predicting school failure was examined by using Cohens Kappa (Cohen, 1960) after

$$\kappa = \frac{p_o - p_e}{1 - p_e}, \tag{1}$$

with p_o = the proportion of cases where the prediction was correct, and p_e = the proportion of cases where correct prediction is expected by chance. We supplemented calculation of the agreement coefficient kappa with the report of two parameters derived from the binary classification matrix, which were sensitivity and specificity. Both parameters may help controlling for bias and prevalence effects that could occur with kappa due to deviances from even distributions of the marginal frequencies (cf. Hoehler, 2000). Sensitivity is the probability that someone showing the outcome is actually tested positive, and specificity is the probability that someone in absence of the outcome is tested negative.

In the last step of our analysis, we examined whether a simple algorithm, suggested by Gigerenzer and Goldstein (1996), might predict school failure in this sample to a similar degree of accuracy. This algorithm—the take-the-best heuristic—consists of three building blocks, which are a search rule (looking up cues in order of their validity), a stopping rule (stopping search after the first cue discriminates between the options), and a decision rule (choosing the option that this cue favors). For this purpose, we first selected three predictors of the sample which yielded the highest validities (i. e., the highest correlation coefficients) for predicting school failure. These predictors were (a) test scores obtained in mathematics, (b) school marks in mathematics, and (c) engagement in school (see the Results section). We selected only three predictors because fast-and-frugal decision algorithms composed of only three cues have been shown to be as effective in predicting outcomes than linear regression models with a larger number of predictors (Green & Mehr, 1997). Since the take-the-best heuristic is based on alternatives, we converted the values of these three predictors (which were real numbers) into ones and zeros using their median as a cut-off score (cf. Gigerenzer et al., 1999). These ones and zeros were assigned such that the ones corresponded to higher values of the predictors. We constructed three different classification algorithms, depending on the number of predictors involved. TTB 3 entailed all three predictors, TTB 2 only two predictors with highest validities (mathematics test scores and school marks), and TTB 1 only one predictor with the highest validity (mathematics test scores). We reduced the number of predictors because some studies have shown that fairly good predictions of outcomes were achieved even if only two or one cues were used for making these predictions (e. g., Todd & Gigerenzer, 2000).

The construction of the classification algorithm was straightforward. Students were classified as having failed in secondary school if they “scored” on all three (two, one) predictor(s) with zero. This means for TTB 3 that students who were classified as failing obtained below-median scores on the mathematics test, below-median marks in mathematics, and below-median scores on engagement in school. However, if students scored in one of the predictors above median, they were considered successful. Figure 1 shows the fast-and-frugal decision tree with three predictors (TTB 3) for identifying students at risk of school failure.

As with the regression models, predictive validity was examined by using Cohen's Kappa, supplemented by the report of the parameters sensitivity and specificity. We set the significance level in accordance with the usual convention for all analyses to $\alpha = 5\%$.

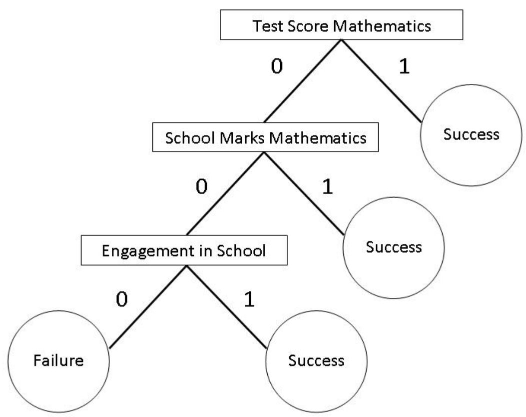

Figure 1. Fast-and-frugal decision tree with three predictors for identifying students at risk of school failure.

0 means under median of the variable, 1 means over median of the variable.

3. Results

3.1 Differences between students at risk and students not at risk

We first wanted to know whether students experiencing school failure and their successful peers differed with regard to the predictor variables used in this study. Table 1 shows the distribution of the qualitative variables in both groups of students.

Table 1. Sample sizes by criterion (failure versus success), gender, ethnicity, and school track

Predictor	**Success**		**Failure**		**All**	
	n	%	n	%	n	%
	2052	100.0	735	100.0	2787	100.0
Gender						
Male	965	47.0	394	53.6	1359	48.8
Female	1087	53.0	341	46.4	1428	51.2
Ethnicity						
Lux	1414	68.9	429	58.4	1843	66.1
Por	346	16.9	177	24.1	523	18.8
other	292	14.2	129	17.5	421	15.1
School track						
Academic	988	48.1	249	33.9	1237	44.4
Vocational	1064	51.9	486	66.1	1550	55.6

Note. Column percentages per predictor sum up to 100.

What can be seen at first glance is that the distribution of all three variables differed between students who succeeded and students who failed. There were more girls than boys in the success group, but more boys than girls in the failure group. Moreover, the percentage of immigrant students was lower in the success group than in the failure group.

Finally, the number of students attending the academic track was much higher in the success group than in the failure group. Chi-square tests revealed that all differences in the observed frequencies were significant ($\chi_{Gender} = 9.37$, $p = .002$; $\chi_{Ethnicity} = 28.08$, $p < .001$; $\chi_{School\ track} = 44.65$, $p < .001$; all test were two-tailed).

We additionally were interested in differences in the metric predictor variables between both groups of students. Table 2 shows the means and standard deviations of the metric predictors.

As with the qualitative predictors and in line with our hypotheses, differences in metric predictors became all significant between both groups of students. Students who failed had on average lower school marks and lower achievements in standardized tests than their succeeding peers. Moreover, the former students were on average less engaged, less acquiescent, showed fewer social behaviors, and were older than the latter ones.

Table 2. Means and standard deviations of the metric predictors

Predictor	**Success** $n = 2052$		**Failure** $n = 735$			
	M	*SD*	*M*	*SD*	t^a	p^b
School marks German	47.93	6.54	44.74	6.66	11.17	< .001
School marks French	46.90	6.53	43.69	6.99	10.85	< .001
School marks mathematics	46.46	8.24	41.65	8.61	13.14	< .001
Test score German	0.26	0.76	-0.15	0.78	12.51	< .001
Test score French	0.22	0.79	-0.14	0.77	10.78	< .001
Test score mathematics	0.29	0.89	-0.22	0.84	14.07	< .001
Engagement	3.56	0.47	3.28	0.58	11.67	< .001
Acquiescence	3.65	0.45	3.42	0.57	10.17	< .001
Social behavior	3.64	0.53	3.45	0.63	7.26	< .001
Age (years)	12.49	0.50	12.64	0.56	-6.81	< .001

Note. [a] *t*-tests were conducted by assuming unequal variances. [b] *p*-values represent two-tailed testing.

3.2 Correlation analysis

Prior to regression analyses, we looked at pairwise correlations between the predictors and the criterion. School failure, school track, ethnicity, and gender were entered as dichotomous variables into correlation analysis. The levels of school failure were “failure” (1) versus “success” (0), the levels of school track were “academic track” (1) versus “vocational track” (0), the levels of Luxembourgish students were “Luxembourgish students” (1) versus “other students” (0), the levels of Portuguese students were “Portuguese students” (1) versus “other students” (0), and the levels of gender were “male” (1) versus “female” (0). Table 3 depicts the correlation coefficients.

All predictors were significantly related to school failure. The correlation coefficients mirrored to some extent results from the t-tests. The largest correlation coefficient in regard to school failure was obtained from mathematics test scores, followed by school marks in mathematics. The better the school mark or the higher the test score was, the lower was the probability of failing in secondary school. The remaining achievement variables were also significantly and negatively related to school failure. The smallest coefficient with respect to school failure corresponded to students’ gender. Yet, girls were significantly less likely to fail than boys. As with the t-tests, age, ethnicity, and school track were related to school failure. Younger students, immigrant students, or students attending the vocational track were more likely to experience school failure than were older students, native students, or students on the academic track.

There were large correlations between some predictors. For example, all achievement variables (test scores, school marks) were highly and positively intercorrelated, which points to the fact that they did all measure to some extent the same attribute. Additionally, achievement variables were highly related to the school track the students attended in secondary school. Higher achievements were more likely to occur on the highest track than on the lower tracks. Furthermore, students' ethnicity was associated with achievement, with native students obtaining rather higher achievements than immigrant students. Moreover, students' gender also contributed to school achievements, i. e., girls obtained higher achievements in languages, whereas boys gained higher achievements in mathematics.

Table 3. Results of the correlation analysis

	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 School failure	-.21***	-.21***	-.25***	-.23***	-.20***	-.25***	-.24***	-.21***	-.15***	.14***	-.07***	.06**	-.13***	.06**
2 School marks German	1	.63***	.71***	.75***	.42***	.58***	.53***	.45***	.26***	-.33***	.27***	-.25***	.65***	-.09***
3 School marks French		1	.63***	.46***	.71***	.48***	.51***	.41***	.22***	-.26***	.10***	-.03	.64***	-.07***
4 School marks math			1	.58***	.46***	.73***	.54***	.44***	.24***	-.27***	.19***	-.14***	.63***	.06**
5 Test scores German				1	.47***	.68***	.40***	.29***	.18***	-.30***	.29***	-.26***	.65***	-.05*
6 Test scores French					1	.56***	.39***	.26***	.14***	-.17***	.05*	.01	.60***	-.03
7 Test scores math						1	.42***	.28***	.19***	-.24***	.21***	-.16***	.65***	.09***
8 Engagement							1	.68***	.53***	-.17***	.09***	-.07***	.44***	-.15***
9 Acquiescence								1	.57***	-.09***	.10***	-.06**	.34***	-.27***
10 Social behaviors									1	-.08***	.07***	-.03	.19***	-.29***
11 Age										1	-.15***	.13***	-.29***	.01
12 Ethnicity Lux.											1	-.27***	.21***	.03
13 Ethnicity Port.												1	-.15***	-.00
14 School track													1	-.04
15 Gender														1

Note. *** $p < .001$, ** $p < .01$, * $p < .05$

3.3 Regression analyses

Whether the effects of the predictors obtained from correlation analysis reflected their unique contribution to the prediction of school failure, or rather were dependent on one another, was examined by regression analyses. Table 4 shows the results of the regression analyses.

In Regression Model 1, the largest predictors were the test scores obtained in mathematics and German. Further significant predictors were school marks in German, engagement, acquiescence, and age. Interestingly, for German school marks a positive odds ratio was obtained, meaning that the likelihood for school failure was increased with better school marks when all the remaining variables were controlled for.

Obviously, some variables that were significantly related to the criterion were not predictive for school failure when all variables were considered simultaneously in the regression analysis. This was particularly true for school marks in French, social behaviors, and ethnicity. School marks in French were highly correlated with test scores in French as well as with diverse other variables, so that their effect was partialled out from the whole variance of the criterion.

Table 4. Results of the regression analyses

Predictor	**Model 1**			**Model 2**		
	Odds Ratio	p	Wald	Odds Ratio	p	Wald
Marks German	1.24	.011	6.43	1.26	.030	4.71
Marks French	0.95	.546	0.37	0.78	.017	5.73
Marks math	0.87	.073	3.22	0.71	< .001	13.33
Test German	0.79	.002	9.33	0.66	< .001	23.86
Test French	0.90	.146	2.11	0.82	.012	6.37
Test math	0.78	.003	8.97	0.69	< .001	18.81
Engagement	0.87	.037	4.36	0.84	.025	5.06
Acquiescence	0.85	.007	7.15	0.75	< .001	13.16
Social	0.97	.570	0.32	0.98	.710	0.14
Age	1.15	.004	8.24	1.31	< .001	20.81
Ethnicity: Lux	0.99	.786	0.07	0.96	.480	0.50
Ethnicity: Por	1.04	.394	0.73	1.09	.088	2.91
Gender	1.10	.059	3.55	1.11	.054	3.71
Track				2.36	< .001	97.75
Marks German * Track				1.13	.286	1.14
Marks French * Track				0.91	.384	0.76
Marks math * Track				0.77	.013	6.21
Test German * Track				0.90	.232	1.43
Test French * Track				0.90	.184	1.77
Test math * Track				0.90	.241	1.37
Engagement * Track				0.98	.826	0.05
Acquiescence * Track				0.84	.047	3.96
Social * Track				0.95	.363	0.83
Age * Track				1.18	.010	6.56
Ethnicity: Lux * Track				0.93	.164	1.94
Ethnicity: Por * Track				1.10	.093	2.82
Gender * Track				0.94	.274	1.20
Intercept	0.32	< .001		0.46	< .001	
R^2	.141			.200		
Hosmer-Lemeshow χ^2	20.06	.010		7.81	.453	
Classified correctly (expected)	73.6			73.6		
Classified correctly (Model)	74.6			75.3		

Note. Goodness of fit is expressed by Nagelkerke R^2 and by the Hosmer-Lemeshow index. The Wald statistic is the ratio of the square of the estimate of the regression coefficient to the square of the estimate of its standard error. The larger the Wald statistic is, the larger is the impact of a predictor within a set of predictors. Classified correctly refers to the percentage of students being correctly classified as either showing failure or success.

In Regression Model 2, the track students attended in secondary school was added as a predictor. Moreover, we supplemented interaction terms to the main effects of the predictors, representing the combined effects of each predictor and the track on the criterion. When an interaction effect was present, the impact of one predictor depended on the level of school track, that is, on the particular school track the students attended in secondary school.

Alike in Regression Model 1, significant predictors for school failure were school marks in German (again with an odds ratio larger than one), test scores in German and mathematics, engagement in school, acquiescence, and age. However, some further predictors became significant in Regression Model 2, which were the remaining school marks and test scores and the track. The latter predictor exerted the largest influence on school failure, indicating a more than doubled chance to fail when students attended the highest track, provided that all other variables were controlled for.

Most interaction terms failed to become significant. Exceptions were the interactions with school marks in mathematics, acquiecsence, and age. Concerning school marks, the effect that better school marks corresponded to a lower probability of school failure was stronger when students attended the academic track than when they attended one of the vocational tracks. The same was true for students' acquiescence. However, with age the reverse relationship was observed. Older students were more likely to fail than younger students, but this relationship was strengthened when students attended one of the vocational tracks rather than the academic track.

Compared to Regression Model 1, the model including interaction terms was superior over the first model in terms of model fit, as is evident by comparison of the Nagelkerke R^2 coefficients. However, as with the Nagelkerke index, the Hosmer-Lemeshow index of fit (Hosmer & Lemeshow, 2000), which provides an additional goodness of fit test that examines whether the S-shaped function of the logistic regression function is appropriate for the observed data, was lower for Regression Model 2 than for Regression Model 1.

3.4 Logistic regression versus take-the-best

We further examined how well the take-the-best algorithm, suggested by Gigerenzer and Goldstein (1996), predicted school failure. We constructed three different classification algorithms, depending on the number of predictors involved. TTB 3 entailed all three predictors, TTB 2 only two predictors with highest validities (mathematics test scores and school marks), and TTB 1 only one predictor with the highest validity (mathematics test scores).

Table 5 shows the frequencies for predicted and actual classification of school failure for both the regression models and the take-the-best models, as well as their respective kappa, sensitivity, and specificity values (Note 1).

Table 5 indicates that the percentage of correct classifications was 74.6 with Regression Model 1 and 75.3 with Regression Model 2, thus Model 2 was slightly superior to Model 1. However, both models performed only marginally better than classification was expected by chance. We calculated Kappa for an estimate of agreement between predicted and observed classification (see Cohen, 1960). With Regression Model 1 and Regression Model 2, the agreement coefficient was $\kappa = .152$, and $\kappa = .204$, respectively. The difference between both kappas was above significance level, $p = .172$ (two tailed), thus Model 2 did not prove to outperform Model 1 in predicting school failure even though it took more information into consideration.

Table 5. Classification results for all models applied

	Predicted										
Observed	**RM 1**		**RM 2**		**TTB 3**		**TTB 2**		**TTB 1**		
	S	*F*	*S*	*F*	*S*	*F*	*S*	*F*	*S*	*F*	Total
S	70.4	3.2	69.4	4.2	56.9	16.8	49.6	24.0	40.9	32.7	73.6
F	22.2	4.2	20.6	5.8	15.1	11.2	11.8	14.6	9.1	17.3	26.4
Total	92.6	7.4	90.0	10.0	72.0	28.0	61.4	38.6	50.0	50.0	100.0
κ	.152		.204		.195		.198		.164		
Sensitivity	.159		.220		.424		.553		.655		
Specificity	.957		.943		.773		.674		.556		

Note. Frequencies are percentages. RM—Regression Model, TTB—Take-the-best, S—Success, F—Failure

Applying the take-the-best algorithm produced in TTB 3 68.1 % correct classifications, which was nominally less than obtained from both linear regression models. However, due to the marginal distributions, classification by chance would produce only 60.4 % correct classifications, as opposed to 70.1 % (RM 1) and 68.9 % (RM 2). Again, the agreement coefficient kappa was estimated, which yielded $\kappa = .195$. This value was neither significantly different from the kappa coefficient obtained from Regression Model 1, nor significantly different from Regression Model 2. We applied a two-predictors algorithm by omitting the predictor with the least validity (engagement), and ran again the analysis. Whereas the number of correct classifications decreased (64.2 %), the agreement coefficient increased compared to TTB 3 and yielded a value of $\kappa = .198$. Finally, the TTB 1 algorithm was run and produced again a kappa of $\kappa = .164$. Differences between all kappa values were not significant.

Whereas kappa remained more or less the same, both sensitivity and specificity differed between the models applied, and were reciprocal to each other. The larger sensitivity was, the smaller was specificity. The regression models showed higher specificities than the take-the-best models, whereas those were more sensitive than regression models.

4. Discussion

4.1 Discussion of the results

With this study we aimed at (1) identifying risk factors that predict school failure in secondary school, and (2) comparing two different approaches in making these predictions. Concerning our first aim, two logistic regression models were applied, and their results showed that achievements in primary school were the strongest predictors for school failure. As hypothesized, students obtaining rather low marks and test scores in primary school were more likely to fail in secondary school than were students with rather high achievements. Moreover, students' school related behaviors, such as a lack of engagement and acquiescence, have been shown to significantly predict school failure. However, in contrast to the hypothesis stated, neither students' gender nor their ethnicity played a role in predicting school failure, although correlation analysis indicated significant coefficients. Obviously, achievement variables that shared a large amount of variance with ethnic affiliation and gender attenuated the impact of these variables on school failure. Furthermore, the track students attended in secondary school turned out to be a moderator of the likelihood of school failure. Not only that the track itself was the largest predictor for the criterion, the relationship between some predictors and the criterion also differed between students attending the academic track and those attending the vocational tracks. The obtained odds ratio above unity for school track seemed to indicate the level of difficulty of the different curricula. Students showing similar achievements in primary school, but attending different tracks in secondary school, were more likely to fail on the academic (i. e., difficult) track than on the vocational tracks.

We did not expect better school marks in German to increase the likelihood of school failure. Inspection of both the correlation coefficients and the odds ratios did not reveal any meaningful explanation for this phenomenon. However, we know from this sample that students obtaining good marks in German were predominantly Luxembourgish students, whereas those getting rather low marks were part of foreign ethnic minorities. Previous research has shown (e. g., Klapproth et al., 2013) that Luxembourgish students were more likely to be recommended for the academic track, while immigrant students were more likely to be placed onto the vocational tracks. However, not all students attending the academic track show achievements that are suitable for this track. For example, Klapproth, Krolak-Schwerdt, Hörstermann, and Schaltz (2013) could show that in Luxembourg about 10 % of the students attending the academic track scored lower on standardized achievement tests than their peers attending the vocational tracks. Attending a track for which one is not suitable might result in negative outcomes (Schuchart & Weishaupt, 2004; Tiedemann & Billmann-Mahecha, 2010) and hence could increase the likelihood for school failure.

The observed increase (and decrease) of odds ratios in Regression Model 2 compared to Regression Model 1, resulting in an overall increase of the number of significant effects, might partly be due to suppression effects being present in that model. Suppression means that the relationship between the criterion and a predictor is reduced by the presence of a third variable. Controlling for the third variable in the regression equation will thus result in an increased strength of the relationship between the predictor and the criterion. Suppression occurs if either the correlation between the predictor and the criterion, r_{y1}, or the correlation between the suppressor variable and the criterion, r_{y2}, is less than the product of the other variable with the correlation between predictor and suppressor variable, r_{12} (Cohen, Cohen, West, & Aiken, 2003). Suppression is also present if r_{12} is negative (or positive) whereas r_{y1} and r_{y2} are both positive (or negative). Applying these criteria, it turned out that the school track, which was inserted as a moderator variable, served as a suppressor variable. Whereas the correlations between the criterion and both the track and some achievement indices (school marks, test scores) were all negative, the correlations between the track and achievement indices were positive.

With respect to our second aim, we compared both regression models and a simple algorithm that only considered up to three predictor variables in order to evaluate how accurately the different models predict school failure. The accuracy of prediction of both regression models was low to moderate, but in line with similar evaluations of regression models that predicted failure in school (Casillias, Robbins, Allen, Kuo, Hanson, & Schmeiser, 2012; Lucio, Hunt, & Bornovalova, 2012; Suh et al., 2007).

As hypothesized, the take-the-best models did perform equally well as the regression models. Even when only *one* predictor (the one with the highest validity) was used to predict failure of students in school, the level of accuracy in prediction (in terms of agreement) was approximately as high as when a linear regression model including interaction terms was applied. However, a comparison between both methods of prediction indicates that whereas sensitivity, i. e., the percentage of correctly identified students at risk, was larger with take-the-best than with logistic regression, the reverse was the case with specificity, i. e., the percentage of correctly rejected students not at risk. Moreover, specificity and sensitivity altered with varying numbers of cues entailed in the model. The more cues (on maximum three) were used, the smaller was sensitivity, but the larger was specificity.

4.2 Main Conclusions

Logistic regression analyses showed that primary school achievements in mathematics and languages were the strongest predictors of failure in secondary school, followed by students' age and students' school-related behaviors. Moreover, we could show that in order to correctly predict failure at school, simple algorithms such as the take-the-best heuristic are not inferior to rather complex regression models. Hence, when teachers want to use regular and daily information (and do not want to make use of administering tests or other diagnostic measures), they could benefit from applying these simple algorithms. However, pedagogical considerations should be made with respect to the differences in sensitivity and specificity between the models.

4.3 Limitations of the study and implications for further research

A few limitations of this study should be considered. First, we unfortunately were not able to make use of all information of students to which teachers regularly have access in school. For example, in addition to indicators of achievement such as school marks and test scores, teachers do also and frequently gain information about the students' self esteem, or their learning strategies, which both might be inferred from their behavior, and which have proven to be predictive for school failure (Finn & Rock, 1997; Tait & Entwistle, 1996). Moreover, it would have been enlightening to explore if variables, which were known to be related to school achievement, but which were not normally accessible to teachers, did add substantially to the predictive power of the models used here. For instance, the socioeconomic status of the students which was not (or at least not explicitly) known by the teachers of our study, appeared to be a prominent risk factor in some investigations (e. g., Lucio, et al., 2012; McMillen & Kaufman, 1997). Finally, the slight advantage of the take-the-best over the regression models due to their parsimony might be qualified in larger samples (Gigerenzer & Brighton, 2009).

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Notes

Note 1. Although it has not been part of our research question, we additionally examined the accuracy of predicting school failure with regression models that entailed the same predictors as the take-the-best models. However, accuracy of these models was clearly below that of the complete regression models as well as of the take-the-best models presented here.