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STUDY SUCCESS AND FAILURE OF STEM STUDENTS AND THE CONNECTION TO THEIR LEARNING HABITS

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ABSTRACT

With the educational expansion, ever more students start a tertiary degree. At the École Polytechnique Fédérale de Lausanne, an engineering school, the number of bachelor students increased from 3’713 in 2010 to 6’330 in 2022. However, in Switzerland, a considerable number of students fail to achieve their first university degree – and failure rates are even higher at engineering schools. A weak mathematics background is often identified as the main reason for dropout. In this paper, we are interested to test whether inadequate learning habits are also responsible to some extent for first-year dropouts. To this end, we matched admission data with self-assessed data about learning habits. These learning habits include time management, effort regulation, and the learning strategies of elaboration and organization ($204 \leq N \leq 823$). These scales are based on one of the most often used instruments for self-regulated learning, the Motivated Strategies for Learning Questionnaire, and have been shown to correlate with academic success in various fields (Credé and Phillips 2011).

Using logistic regressions, we find that time management and elaboration are correlated with higher probabilities of study success. Furthermore, higher scores in all learning habits but organization are related to a lower probability to repeat the first year of a bachelor's degree. Thus, together with better math skills, learning habits contribute to more and faster success in STEM fields and thus to higher student retention.

1 INTRODUCTION

The educational expansion that started in the 20th century is still ongoing today, leading to more tertiary education students. Concretely, at our local engineering school, the École Polytechnique Fédérale de Lausanne (EPFL), the number of bachelor students increased from 3’713 in 2010 to 6’330 in 2022. However, access to tertiary education doesn’t equal success, as many students fail to achieve their bachelor’s degree (Bernardo et al. 2021). Contrary to other countries, where access to engineering schools is based on an admission exam, in Switzerland, access is granted to any Swiss student with a high school diploma. Therefore, at EPFL, the failure rate for the first year is close to 35%, and of the successive sample only around 70% of the students succeed the first year on the first attempt. Weak background in mathematics is often identified as an important factor for dropouts in engineering. However, in this study, we are interested to test whether inadequate learning habits are also responsible to some extent for first-year dropouts. Researchers at EPFL have developed a tool that assesses students’ learning strategies and gives feedback thereupon to support students in their learning. As one of the first steps in validating this tool, we analyze whether the assessed learning habits relate to study success and failure measures.

1.1 Why university dropout matters: Preventing personal and societal costs

One of the oldest claims of why reducing dropout rates matters, especially in STEM fields, exists at least since the end of the Second World War (Smith and White 2019): As it goes, there is not enough supply of highly skilled STEM people for an innovative, growing economy or for basic research. However, Charette (2013) shows that even though there are a prognosticated 277’000 STEM vacancies per year in the United States, there are also more than eleven million people with a STEM degree in the US working outside of STEM, and more than half of the people working in STEM do not hold (and probably not need) a corresponding tertiary degree. Similarly, for the UK context, Xue and Larson’s (2015) analysis of the STEM labor market paints a heterogeneous picture, with shortages e.g. in software development and data science, and surpluses, especially in the academic sector.
Thus, the STEM crisis argument only holds partially, and from other perspectives, dropout might even be desirable. From a practical perspective, there might not be enough space to accommodate all students or over-enrolment might lead to a student-teacher imbalance and, hence, bad student support service. From an elitist perspective, one can assume that good higher education institutions in Europe are characterized specifically by a higher failure rate – as a valuable good, i.e., a degree from a prestigious university, is a sparse good. While these arguments can be contested (e.g., remote teaching in case of space problems; training more teacher assistants for student support), a more severe problem comes from a macro-sociological functionalist perspective: the claim of grade and degree inflation. That is if ever more students are admitted to a tertiary degree and all would graduate (with higher grades), then a university degree loses its information for allocating human resources adequately in the labor market, which is a central function of the educational system. However, supporting students also has clear societal and personal benefits. The education of students who finish their studies faster costs the taxpayer less than when students start several studies without finishing. Also, students who graduate will earn more and consequently pay more taxes, and need fewer welfare subsidies. From a personal development perspective, two issues need to be mentioned. First, many mental disorders emerge in the mid-20s (Kessler et al. 2007). Next to being a driver for school or university dropouts, mental disorders might also be reinforced through dropouts (Ramsdal, Bergvik, and Wynn 2018). Dropouts

might be reduced by adequate social support or induced social gatherings that spark peer support (cf. Stadtfeld et al. 2019). Second, and to counter the argument of degree inflation, retention should always go hand in hand with fulfilling academic skills requirements. Meta-analyses have shown that study skills relate to academic success and, importantly, that study skills can be taught (Jansen et al. 2019). Thus, a better understanding of which study skills are most predictive of dropout in STEM studies might contribute to the design of a support program for struggling students so that the dropout rate can be reduced while the required academic level is still achieved.

1.2 Inadequate learning strategies as drivers of university dropouts

The underlying assumption of the Learning Companion, the tool developed by researchers from EPFL, is that first-year students need to adapt from learning at high school to learning at the university level (Tormey et al. 2020). In high school, students are used to solving routine problems, where they might shortly scan the problem and then try to apply a predefined method. At the university level, they often face problems that they must first analyze, and design a suitable method for effective problem-solving. This problem-solving process requires increased metacognitive skills like planning, monitoring progress, and regulating learning strategies. Thus, students are often ill-equipped when entering university, and teaching them the right learning strategies might help them complete their degree.

Research on self-regulated learning and learning strategies in tertiary education has been abundant, leading to meta-analyses with hundreds of studies (Jansen et al. 2019, Richardson et al. 2012). Nevertheless, the present study can contribute to existing research in two ways: First, studies on self-regulated learning in STEM courses, explicitly, are rare (see Jansen et al. 2019). Second, the dependent variables in studies on self-regulated learning are generally either performance in course exams or grade point averages, but not failure/dropout and success in a tertiary degree (though, there is a new research branch on dropout in massive open online courses).

Regarding study findings, one meta-analysis focusing on the Motivated Strategies for Learning Questionnaire (MSLQ) shows that general skills such as time management, effort regulation, and metacognitive self-regulation seem to be more important for academic performance than specific learning strategies such as rehearsal, critical thinking, elaboration, and organization (Credé and Phillips 2011). Thus, those three most effective learning strategies were chosen for analysis in this study. We also consider elaboration and organization because these are scales assumed to depict deep learning strategies (McKenzie, Gow, and Schweitzer 2004) and are necessary for self-regulated problem-solving which is crucial for success in traditional STEM courses. Credé and Phillips (2011) argue that specific learning strategies might play a different role for weak and strong students and might not have a linear relationship with academic performance. Thus, it merits investigating the relationship between study strategies and study success for weak and strong students separately.

This leads us to the following hypotheses: 1) Metacognitive self-regulation, time management, effort regulation, elaboration, and organization are facets of learning habits that help undergraduate students succeed in their first bachelor’s year; 2) Higher scores on those learning habits shorten the time necessary to complete the first year; 3) Weak and strong students benefit differently from higher scores in learning habits.

2 METHODOLOGY

2.1 Data source, data collection, and sample description

Students from EPFL are sent letters during the summer break before their first semester and invited to fill out a self-assessment questionnaire about their learning habits. The goal is to give them feedback on how they fare in their learning habits and where they might improve to get through their studies. Scores on learning habits are extracted from the developed online tool, the Learning Companion. Additionally, data on gender, type of baccalaureate, registered inscriptions to courses, and national background were provided from study admission and merged with data on learning habits. In total, 1257 students filled out at least one scale on the Learning Companion. Exactly two third of the sample are men and one-third are women. Forty-nine percent of the sample went to high school in France and 22% completed high school in Switzerland with a focus on physics and applied mathematics. The rest did a Swiss baccalaureate with a focus on biology and chemistry (12%), an unspecified different focus (10%), or come from a foreign country other than France (7%).

2.2 Measures

Dependent variables. Success in the first bachelor's year and the duration to complete it is inferred from the data on registered inscriptions to courses. Data on inscriptions is provided on the level of the semester, thus, BA1 and BA2 designate the first year. After a failed first semester, some students take a course to improve their maths skills (in French called *mise-à-niveau*, MAN) before they try the first year again. Success in the first bachelor's year is assumed by reaching BA3, and study failure is assumed in case of discontinuation of inscription before BA3, that is, success in the first year can be achieved after MAN or other repetition, in which case the duration to complete the first year of study is longer than one year. Thus, the dependent variables are success/failure in the first year (coded as 1 = success and 0 = failure), and duration to complete (coded as 0 = two or fewer semesters needed to complete and 1 = needed more than two semesters to complete). Only students that did succeed in their first year are included in the analysis of the duration of it.

Independent variables. The type of baccalaureate was used to group students into students with weak and strong math backgrounds. Students who completed their baccalaureate in Switzerland in physics and applied mathematics as well as students from France (who had to pass a demanding admission test) were rated as having a strong math background. All other students were rated as having a weak math background.

The Learning Companion contains scales on study attitudes and habits and relies on existing questionnaires as well as on self-invented items. The analysis of this paper only includes learning habits scales borrowed from the MSLQ by Pintrich et al. (1991) translated into French. These scales are metacognitive self-regulation, elaboration, organization, effort regulation, and time and study environment. Every scale of the questionnaire can be filled out separately. Table 1 shows how many students participated in each scale. The construction of the scales has been criticized before (Credé and Phillips 2011). Therefore, we also allowed ourselves to make meaningful adjustments for one scale.

For instance, the original time and study environment scale from the MSLQ contains six items on time management and two on study environment but, it is unclear why study time and environment should form one factor. In our factor construction, we disregarded the two items of the study environment and called this factor time management (see a description of all scales in Table 1).

Table 1. Description of the MSLQ scales used

Scale	**Nº items**	**Cronbach's α**	**n**	**Description of the scale and example items**
Metacognitive self-regulation	12[1]	0.71[1]	727	Assesses metacognitive skills such as planning, monitoring, and regulation. Example item: When reading for this course, I make up questions to help focus my reading.
Time management	6	0.68	333	Assesses whether students make good use of study time, do assignments, attend classes. Example item: I find it hard to stick to a study schedule.
Effort regulation	4	0.68	333	Measures the ability to keep working even in case of boredom, distraction, or challenges. Example item: I work hard to do well in this class even if I don't like what we are doing.
Elaboration	6	0.68	204	Measures whether students connect different sources, use previous knowledge to situate new information, or apply new information to the real world. Example item: I try to understand the material in this class by making connections between the readings and the concepts from the lectures.
Organization	4	0.65	823	Measures whether students organize new information in schemes, diagrams, charts, or if they summarize important concepts. Example item: When I study for this course, I go over my class notes and make an outline of important concepts.

[1] The original scale consists of 12 items. However, after confirmatory factor analysis we excluded one item. Cronbach's α refers to the scale with the 11 remaining items.

2.3 Data analysis

We calculated the latent concepts separately for each study habit using confirmatory factor analysis (CFA). We obtained acceptable to good model fits for every scale. However, we had to exclude one item ("I often find that I have been reading for class but don't know what it was all about.") and correlate the error terms of four pairs of items for metacognitive self-regulation; we correlated the error terms of one pair of items for elaboration and organization and for two pairs of items for time management. To be able to compare the latent scores of the scales for students with weak and strong math backgrounds, we tested for and could approve scalar measurement invariance (MI, see table 2 for model fits). The CFAs with scalar MI constitute our final models and are used to predict the latent variable scores, which were then subsequently used for logistic regressions. Model fits are deemed good when satisfying the following values: p-value of χ^2 is >.05, robust CFI > .95, robust RMSEA < .06, SRMR < .08 (Hu and Bentler 1999).

Table 2. Model fits of scalar measurement invariant CFA of the learning habits for the groups of students with strong and weak math backgrounds

Scale	**n**	***df***	χ^2	***p***	**CFI**	**RMSEA**	**SRMR**
Metacognitive self-regulation	727	100	169.9	<.001	0.922	0.046	0.052
Time management	333	24	33.5	.093	0.958	0.055	0.052
Effort regulation	333	10	10.4	.407	0.998	0.017	0.035
Elaboration	204	26	15.1	.955	1.000	0.000	0.050
Organization[1]	823	7	7.1	.419	1.000	0.006	0.021

[1] reached partial scalar measurement invariance: intercept of one item was set to vary between the two groups. Note: multivariate distribution of the scales was non-normal, therefore, maximum likelihood estimation with robust standard errors and a Satorra-Bentler correction was used. We report robust values for CFI and RMSEA.

For both dependent variables, success/failure in the propaedeutics and duration of propaedeutics, we performed a series of logistic regression analyses with each learning habit separately. First, we tested a null model, then we introduced the learning habit to see if this has any predictive effect. Third, we introduced the group variable of weak and strong math backgrounds to see if those groups have significantly different probabilities to succeed or repeat. And fourth, we tested an interaction effect between the learning habit and the group to analyze whether the learning habits have different effects for the two groups regarding their probability to succeed or repeat during the propaedeutics. We run analyses of deviance to select the best-fitting model for each learning habit.

3 RESULTS

3.1 Success and duration of the first year

As mentioned in the introduction, the failure rate in the first year at EPFL is close to 35%. Some of those students drop out after their first semester. A second group of students drops out after the MAN semester, and a third group drops out after repeating the full first year of study. Once students make it to the second year, they hardly fail anymore.

Our analyses, presented in Table 3, show only partial support of hypothesis 1: time management and elaboration are significant factors for study success in the first bachelor’s year, however, effort regulation, metacognitive self-regulation, and organization do not contribute toward a higher probability of success in the first year.

Table 3. Best-fitting logistic regressions

Learning habit	**DV**	**n**	$\boldsymbol{\beta}_{\text{learnstrat}}$	$\boldsymbol{p}_{learnstrat}$	$\boldsymbol{\beta}_{\text{group}}$	$\boldsymbol{p}_{group}$
Metacognitive self-regulation	Success	727	0.054	.102	0.137	<.001
	Duration	536	-0.157	.003	–	–
Time management	Success	333	0.077	.020	0.167	<.001
	Duration	248	-0.161	.001	–	–
Effort regulation	Success	333	0.026	.267	0.172	<.001
	Duration	248	-0.085	.011	–	–
Elaboration	Success	204	0.142	.003	–	–
	Duration	154	-0.282	<.001	–	–
Organization	Success	823	0.022	.130	0.187	<.001
	Duration	607	–	–	–	–

Note. DV = dependent variable; β_{group}: reference group is weak math background

Support for hypothesis 2 is present for all learning habits but organization: higher scores in learning habits generally shorten the time to completion of the first year. Finally, hypothesis 3 that learning habits affect academic performance differently for weak students than for strong students cannot be supported. The estimates for the interaction effects were all found to be non-significant. Table 2 shows that when controlling for the respective learning habits, students with a stronger math background have a higher probability of success than those with a weak math background (except for elaboration). Additionally, t-tests on the learning habits for the two groups indicate that students with a stronger math background score significantly higher – with the exception of organization (p = .203). Effect sizes of these significant differences in learning habit scores are small, ranging from Cohen's d = 0.24 for time management to 0.35 for elaboration.

3.2 Discussion

The analyses lend partial support to our hypotheses and are generally in line with existing research linking self-regulated learning with course performances or grade point averages. Success in the first year depends not only on inferred math background but also on time management skills and the learning strategy of elaboration. Regarding previous research, it is a bit surprising that effort regulation is not a significant contributor to study success, as this factor usually has one of the highest correlations with grades (Credé and Phillips 2011). Furthermore, higher scores in the measured learning habits are related to a shorter duration needed for completion – except for the learning strategy organization. This finding seems to indicate that training students to develop their learning habits is a good investment for universities to reduce the overall length of studies. In sum, we can assume that higher math and certain learning skills positively impact the probability of success. At EPFL, supporting students with their math skills is already institutionalized with the MAN semester offered to students who fail the first semester. However, student retention might be improved by providing more diverse or tailored study courses to struggling students, as 56% of the students taking a MAN semester are students with a strong math background, and still, only 31% of all those taking a MAN semester succeed in the end. It is also noteworthy that students with an assumed stronger math background generally score higher in those learning habits, and students with a strong math background and high scores in learning habits have especially high success probability. This indicates that a specially designed semester that should close the gap between failing and succeeding students should not only focus on math skills but also on learning habits. A book on "learning to study" (Tormey and Hardebolle 2017) and a MOOC were produced supporting the online self-assessment tool. However, we lack evidence on the adoption of those media by our students and further dissemination should be fostered. For example, during the MAN semester, some hours might be dedicated to developing impactful learning habits using those media.

This research also yields three limitations. First, the internal consistency of the scales is rather low for a commonly used instrument (MSLQ). Second, there seems to be a self-selection bias to fill out the questionnaire at least to some degree: more students succeed in the propaedeutics in our sample than of the full student population (78% vs. 66%), the percentage of students who did MAN in our sample is double as high as in the full student population (35% vs. 17%), and in the analyzed sample only 29% of the students are assumed to have a weak background in mathematics, while in the full population, it is 39% of the students. Third, the true relationship between the dependent and independent variables might be stronger than our results suggest, as study failure or success is a global measure, while the MSLQ measures are course specific (Credé and Phillips 2011).

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