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Note to first-year university students: Just do it! In the end, the fact *that* you study may be more important than *how* you study

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Abstract

Education is important to society, yet many students do not complete the educations they start. In the present study of 426 students at a Norwegian university, we examined the predictive value of study-related variables with regard to student status one and five years after initial enrollment (stayers versus dropouts). The logistic regression analyses indicated that older students and students who spent less time studying were more likely to drop out after the first year. Students who completed less ECTS during the first year were more likely to drop out after five years. Contrary to our hypothesis, learning approaches and procrastination were not significant predictors for dropout. Overall, just studying and staying (on) the course mattered more for student success in the first year than self-reported measures on how the academic work was actually done. A caveat relates to the low response rate of the study (~9%), which is addressed in the discussion.

Keywords
dropout, higher education, learning approaches, academic achievement, procrastination

Introduction

As the number of students entering higher education is expanding (OECD, 2020), the student population is also becoming more heterogeneous. Although this change is mostly positive (Belfield & Levin, 2007; Putnam, 2015), a downside is a concomitant increase in dropout rates. In Norway, one-third of enrolled students do not complete their degrees within eight years of first enrolling (Statistics Norway, 2021). This is alarmingly high. To curb this, we need to expand our understanding of potential underlying risk factors.

We therefore sought to map, throughout participants' university studies, connections between relevant demographics, student approach to learning (SAL) and procrastination, any trajectory changes (uniquely available through Norway's thorough student registry database), and student study program outcomes. We also investigated predictors of university dropout during the first and fifth years, and examined to what extent their patterns may be interrelated or separate.

The definition and monitoring of dropout warrants some consideration as students exiting a study program commonly continue at another program or at another institution, despite changing (terminating) their original plan (Heublein, 2014; Hovdhaugen & Aamodt, 2005; Rodríguez-Gómez et al., 2016). After leaving their first institution, they may well complete a degree on a second attempt another place. This is called *institutional dropout* or *transfer-outs,* as opposed to *system dropout* where students completely drop out of the educational system (Rodríguez-Gómez et al., 2016). Another possibility is *stop-out*, where students temporarily leave and later return to a program.

We defined system dropout as students who exit their original study program without a degree and do not show up in another study program or institution within six years after first entering university. Institutional dropouts enrolled at another educational program are, on the other hand, regarded as stayers. Norway has a noteworthy tool for monitoring students' educational journeys both within and between institutions – the National Database for Statistics on Higher Education (DBH). DBH provides high-quality register data that enable correct dropout classification over time.

The present study collected data from domains that prior research had shown to be related to lower academic performance in general and, to some extent, to system dropout directly. *Study-related* variables include procrastination, student approaches to learning and hours per week spent on studying, and *academic performance* variables include grades and the number of credits earned. Then we examined their joint contribution to system dropout.

Marton and Säljö (1976), Biggs (1979) and Entwistle (1979) have identified three types of learning approaches that characterize student learning: deep, surface and strategic. The deep learning approach is characterized by seeking meaning and trying to understand the material, while the surface approach is characterized by focusing on exam expectations and performance and rote learning. The strategic approach is characterized by a focus on time and resource management. This approach may accompany or balance the use of either one of the others. Learning approaches have been connected to study performance (Richardson et al., 2012; Schneider & Preckel, 2017): Deep and strategic approaches have been found to be positively associated with performance while surface approaches have been found to be negatively associated with performance (Diseth, 2007; Duff et al., 2004; Reid et al., 2007). Learning approaches have also been found to be related to self-regulation (Heikkilä & Lonka, 2006). Students with a deep learning approach typically report more optimism and better self-regulation, which, in turn, is associated with less task avoidance. Heikkilä et al. (2011) argue that this indicates a close relationship between learning approaches, success expectations and self-efficacy. Self-efficacy, in turn, has been found to predict dropout (Bager-Elsborg et al., 2019). The direct relationship between approaches to learning and dropout is, however, not clear, and justifies our further investigation.

Another study-related behavior is procrastination – voluntarily delaying a task despite knowing that it most likely will worsen the outcome (Steel, 2007). Several academic environment characteristics may contribute to them becoming "procrastination friendly", including distant deadlines, large degrees of student freedom, temptations and distractions, and low focus on skills training (Svartdal et al., 2020). Not surprisingly, procrastination has been linked to a decrease in academic life satisfaction (Balkis, 2013), but also to other study-related factors (Steel, 2007). Bäulke et al. (2021) found significant positive correlations between academic procrastination and five phases of intention to quit studies (non-fit perception, thoughts of quitting, deliberation, information search and final decision). In a recent Norwegian paper, the link between self-efficacy, procrastination and dropout intentions was investigated, concluding that lower self-efficacy was associated with procrastination and that procrastination was associated with dropout intentions, but also that academic procrastination mediated the relationship between self-efficacy and dropout intentions (Nemtcan et al., 2022).

Given the consistent negative association found between procrastination and self-efficacy, study skill habits and academic performance (Nemtcan et al., 2022; Steel, 2007; Svartdal et al., 2021), and with dropout intentions (Bäulke et al., 2021; Nemtcan et al., 2022), we have reason to suspect that procrastination may play a role in actual academic dropout as well.

Grade Point Average (GPA) scores are perhaps the most important predictor for dropout (Araque et al., 2009; Borgen, 2012), and should therefore be included both for predictive and adjustment purposes. GPA is not only an indicator of what the students have learned but also of how well they have learned to learn. However, GPA does not tell us whether the students are following normal or delayed progression. We therefore also included the number of European Credit Transfer and Accumulation System (ECTS) credits earned during students' first year of study to account for that.

Based on this review of relevant variables, we expect that use of surface learning approaches and extensive procrastination will predict dropout. We also expect that greater reliance on deeper or strategic learning approaches will counteract dropout, along with the earning of more ECTS academic credits and having a higher GPA.

Materials and Methods

Participants and Procedure

We conducted a prospective study using a combination of survey responses (predictors) and registry data (predictors and outcome). With the goal of recruiting a heterogeneous sample, all first-year students enrolled in any study program at our university – a traditional Norwegian university which offers both professional study programs and broader discipline degrees – during fall 2013 ($N = 4616$) were invited to participate via email. Those who consented ($n = 555$) received a URL link to the web survey (www.questback.no), to which 430 responded. Four students were excluded (two withdrew their consent, one was not formally enrolled, and one was enrolled at a PhD program).

The responding students were distributed over a range of subjects: Medicine and dentistry (4.7%); other health subjects (12.7%); psychology (16%); science, technology, engineering and mathematics (13.4%); teacher education (12%); economy, management, leadership, and tourism (11.3%); marine subjects (2.3%), law (4.9%); other social sciences (8.2%); music and art (2.1%); culture and language (5.9%), other humanities (3.8%); and other (2.8%). Half of the participants (49%) were enrolled in bachelor's programs, 27 % in one-year programs or single subjects, and 24% in master's programs.

To determine the representativeness of this sample, the university registries gave us access to de-identified data related to age, gender and incoming GPA, thus enabling a non-response analysis. The mean age of the non-responders ($M = 26.1$, $SD = 8.3$) was not significantly differently from responders ($N = 426$, $M = 25.4$, $SD = 8.4$; $t_{4611} = -1.58$, $p = .11$). The responder group had a significantly higher proportion of women than the non-responders' group (67.5% vs. 58.9%; $\chi^2{}_1 = 12.34$, $p = .001$). Responders had a higher mean GPA from upper secondary school (range 0–6, $M = 4.1$, $SD = 0.72$) than non-responders ($M = 4.0$ and $SD = 0.66$); however, the effect size magnitude was minor (Cohen's $d = .15$, $t_{2791} = 3.37$, $p = .001$).

The study was approved by the Norwegian Social Science Data Services (ref.: 34867/3/LT).

Measurement

Registry data about student status were provided by the National Database for Statistics on Higher Education (DBH), which records information about study program choices and student educational status (in which study program, if any, they are registered). We received data for ten subsequent semesters after enrollment in fall 2013 (spring 2014–fall 2018), including how students migrate between programs or institutions, since the DBH registers information from all higher educational institutions in Norway. The dropout variable encompassed two groups of students. The reference category (coded 0) included all students who were still studying, had achieved a degree, or who only registered for single subjects in the first place (see Table 1). The contrast category (coded 1) defined students who had dropped out, i.e. were not enrolled at any study program in fall 2018 and had not completed their degree.

Table 1. Status fall 2018, N = 426

Status	Percent	Category*
Completed	55.2	0
Transferred to another program or institution, still enrolled	11.3	
Still enrolled and on time	4.2	
Still enrolled, but delayed	2.8	
Only single subjects intended	7.0	
Dropout (not active fall 2018 and not completed the degree)	19.5	1

Note. The majority (89.7%) started at a new study program during fall 2013; 49.1% had been enrolled in higher education before, and 9.1 % had completed a degree.
* Category used for the logistic regression analyses.

The demographic variables included age, gender, and the parental level of education (categorized as mandatory school, upper secondary, or higher education). Learning approaches were measured with the Approaches and Study Skill Inventory for Students (ASSIST; Entwistle, 1997; Tait & Entwistle, 1996). We used a Norwegian validated short version with 24 items (Diseth, 2007). As described in a previous article treating the same questionnaire data material (Sæle et al., 2017), we excluded seven items based on the results of a principal component analysis (PCA). Cronbach's αs were .74 (deep), .61 (surface) and .82 (strategic), which vary somewhat from Entwistle's (1997) original measures in English (Cronbach's α = .84, .80, .87, respectively). The deep learning approach variable was moderately left-skewed (−.75).

Procrastination was measured with the Norwegian form of the nine-item Irrational Procrastination Scale (Steel, 2010), which addresses time-spending and postponing behavior. Support of both convergent and divergent validity is available (Steel, 2007; Svartdal, 2015). Cronbach's α was .84, which is a little lower than the original studies ($\alpha = .91$ in Steel, 2010).

As an estimate of workload, students provided information on the number of hours per week spent on studying.

As a measure of academic performance, we included the GPA based on ECTS-weighted grades from all exams completed during the first study year. We transformed the A–F letter grades to 5–0 (A, 5; F, 0). Pass/Fail grades were coded as C/F, i.e. 3/0 points. We also calculated the total number of ECTS passed during the first year as an indication of how fully they followed the normal study program progression. The normative amount of ECTS academic credits for one year (two semesters) is 60, which 44% of our sample completed (range: 0–100). In some study programs, exams covering the whole year are given at the end of the spring semester. Hence, we calculated GPA and ECTS based on data from both fall 2013 and spring 2014. Finally, we included transfer as a variable – that is, if students at any point since 2013 had transferred to another study program (coded 1 in the analyses), another institution (2) or both (3).

Statistical Procedures and Analyses

We used R and SPSS version 29 for statistical analyses (IBM Corp, 2019; R Core Team, 2021). All questions in the web-based survey were mandatory, and DBH/the university provided complete registry data, hence there were no missing data. An exception was GPA, which we did not calculate for 46 students because they had pass marks exclusively or had not completed any exams during the first year.

We calculated Pearson correlations between continuous variables and Spearman's rho between categorical variables.

Logistic regression analyses were conducted. In the first analysis, dropout after the first year represented the outcome variable. The first model included learning approaches, procrastination, and study hours, while the second model controlled for age and gender. The second logistic analysis was similar but replaced the outcome variable with the dropout status after five years. Here, we added an additional model by including academic performance (earning of ECTS points, and GPA scores from the first study year). As dropout rates may vary between subjects of study, we adjusted for it by adding it as a random intercept factor given that it contributed significantly.

Results

One year after enrollment 14.5% of the students were not registered at any Norwegian university. That number increased to 19.5% after five years. The distribution of student status for each semester is shown in Figure 1, while Table 1 shows the detailed status for fall 2018.

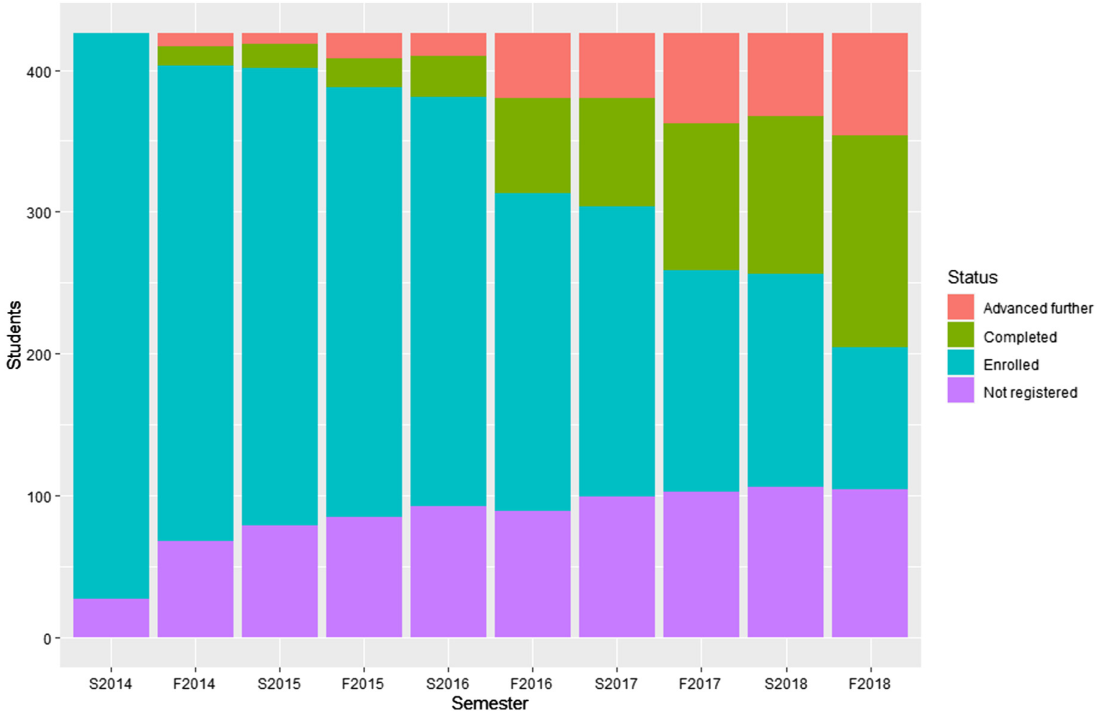

Figure 1.

Half of all students (49.2%) had switched to another study institution or study program, or both. The number of transfer students was similar within the two outcome categories, indicating, importantly, that transfer does not, in itself, increase dropout ($\chi^2 = 4.137(3)$, $p = .247$).

Correlations

Correlations between the variables are presented in Table 2. The strongest correlations were between procrastination and strategic learning approach ($r = .66$), ECTS the first year and dropout after the first year ($r = .41$), ECTS and GPA ($r = .45$), and strategic learning approach and weekly study hours ($r = .38$). All variables correlated significantly with GPA (e.g., procrastination, $r = -.16$; deep learning approach, $r = .24$; surface learning approach, $r = -.13$, strategic learning approach, $r = .22$), including the outcome variables (dropout after the first year, $r = -.17$; dropout after the fifth year, $r = -.15$).

Table 2. Correlations between variables

Variable	1	2	3	4	5	6	7	8	9	10
1. Dropout 2014 (0/1)										
2. Dropout 2018 (0/1)	.33***									
3. Procrastination (1–5)	.05	.06								
4. Deep learning approach (1–5)	−.04	−.06	−.15***							
5. Surface learning approach (1–5)	−.03	−.09	.28***	−.18***						

Variable	1	2	3	4	5	6	7	8	9	10
6. Strategic learning approach (1–5)	−.03	−.08	−.66***	.33***	−.19***					
7. Weekly study hours (1–55)	−.27***	−.13**	−.21***	.11*	.00	.38***				
8. ECTS first year (0–100)	−.41***	−.26***	−.11*	.14***	.01	.14***	.26***			
9. GPA first year (0–5)	−.17**	−.15**	−.16***	.24***	−.13*	.22***	.19***	.45***		
10. Age	.19***	.20***	−.09	.17***	−.16***	.11*	−.23***	−.31***	−.09	
11. Gender (male = 0; female = 1)	.06	−.09	−.05	.01	.09	.14**	−.04	.04	.06	−.09
Mean for continuous variables			3.05	4.13	3.14	3.57	23.50	43.97	2.95	25.39
SD for continuous variables			0.86	0.59	0.84	0.93	12.63	23.33	1.17	8.37

Note: Pearson's r is reported for continuous variables, Spearman's rho for categorical (dropout 2014 and 2018; gender). $N = 426$ on all variables except GPA ($N = 380$).
* = $p < .05$, ** = $p < .01$, *** = $p < .001$.

Predictors of Dropout After One Year

The logistic regression analysis was specified with dropout after the first study year as the outcome variable. Among the study behavior variables, only the amount of study hours per week predicted dropout. The relationship was non-linear (a quadratic effect) showing a quick deceleration in the probability of dropout the more hours spent studying, and with a flattening of the curve around 30–35 hours of weekly studying, after which the probability of dropout again increased (see Figure 2 for illustration).

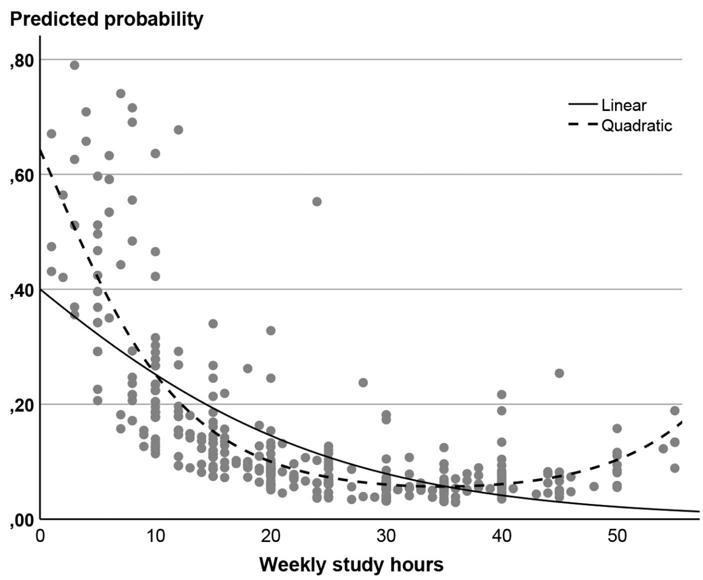

Figure 2.

This implies that the risk of dropout accelerates markedly the less hours a week a student spends on studying, which reaches approximately 40% among students only studying four to five hours a week. In the second/final model, the non-linear effect of study hours remained significant along with age (with older students having higher odds of dropout). The overall accuracy of the model was 74.2% with a higher risk of predicting a false positive (20.4%) than a false negative (5.4%) case (see Table 3). We also adjusted for pre-university GPA and choice of university study program, but as these covariates produced poorer model fit, they were discarded. The adjustment for study subjects, as a random intercept factor, was not significant and hence not included in the final model.

Table 3. Logistic regression on dropout after one year of studying

	Model 1 (N = 426)	**Model 2 (N = 426)**	
	OR [95% CI]	***beta***	**OR [95% CI]**
Intercept		−1.74	
1: Study behavior			
Procrastination (1–5)	1.33 [0.8, 1.97]		
Deep approach (1–5)	0.95 [0.57, 1.5765]		
Surface approach (1–5)	0.91 [0.64, 1.29]		
Strategic approach (1–5)	1.41 [0.91, 2.20]		
Weekly study hours (1–55)	0.81 [0.75, 0.88]***	−0.166	0.85 [0.78, 0.92]***
Weekly study hours-squared (1–55)	1.003 [1.001, 1.005]***	0.002	1.002 [1.001, 1.004]**
2: Demographics			
Age (18–66)		0.058	1.06 [1.03, 1.09]***
Gender (♂ = 0, ♀ = 1)		0.519	1.68 [0.85, 3.31]
Random effect (study subject)			logit var = 0.311 (SE = 0.301)^{ns}
Model fit			
Pseudo R^2: Cox & Snell; Nagelkerke	0.07; 0.13		0.11; 0.20

Notes. Overall accuracy = 74.2% (false positive/negative rate = 20.4%/5.4%). Hosmer-Lemeshow test (p = 0.73). *beta* = log odds (or logit) coefficient. The addition of a random factor accounting for variance in dropout rates across the 13 study subjects was not significant, hence not needed for adjustment purposes. Variables with p-values > .05 were removed in the subsequent model. ^{ns} = not significant, * = $p < .05$, ** = $p < .01$, *** = $p < .001$. Coefficients may be converted to a probability for dropout as follows: probability = 1/(1 + exp((intercept + $beta_1$*StudyHours + $beta_2$*StudyHours*StudyHours + $beta_3$*Age + $beta_4$*Gender))). A woman who is 26 years old would have a dropout probability of 38.2% (given 5 hrs/week), 16.1% (given 15 hrs/week) or 4.4% (35 hrs/week).

Predictors of Dropout After Five Years

When using dropout as recorded five years later, the non-linear effect of study hours per week again contributed significantly with a similar pattern as for the one-year dropout data, and tentatively along with greater use of the surface approach in the first model (see Table 4). When adding academic performance, ECTS contributed significantly while surface approach turned non-significant. ECTS stayed significant also after including age and gender as covariates, but the non-linear effect of study hours was not retained in the final model. The ORs and model fit indices are reported in Table 4. The adjustment for study subjects, as a random intercept factor, was not significant and hence not included in the final model. The overall accuracy of the model was 69.0% with a higher risk of obtaining a false positive (22.8%) than a false negative (8.2%) case.

Table 4. Logistic regression analysis on dropout after five years of studying

	Model 1 (N = 426)	Model 2 (N = 380)	Model 3 (N = 426)	
	OR [95% CI]	OR [95% CI]	*beta*	OR [95% CI]
Intercept			−0.63	
1: Study behavior				
Procrastination (1–5)	1.32 [0.89, 1.96]			
Deep approach (1–5)	0.77 [0.49, 1.19]			
Surface approach (1–5)	0.74 [0.55, 1.02]†	0.88 [0.63, 1.25]		
Strategic approach (1–5)	1.10 [0.74, 1.61]			
Weekly study hours (1–55)	0.890 [0.829, 0.956]***	0.896 [0.825, 0.974]***		^{ns}
Weekly study hours-squared (1–55)	1.002 [1.001, 1.003]**	1.002 [1.000, 1.004]**		^{ns}
2: Academic performance				
ECTS		0.982 [0.967, 0.997]*	−0.026	0.975 [0.964, 0.985]***
GPA		0.80 [0.62, 1.05]		
3: Demographics				
Age (18–66)			0.02	1.02 [0.99, 1.05]
Gender (♂ = 0, ♀ = 1)			−0.43	0.65 [0.39, 1.10]
Random effect (study subject)			logit var = 0.077 (SE = 0.124) ^{ns}	
Model fit				
Pseudo R^2: Cox & Snell; Nagelkerke	0.03; 0.05	0.05; 0.09		0.08; 0.12

Notes. Overall accuracy = 69.0% (false positive/negative rate = 22.8% / 8.2%). Hosmer-Lemeshow test ($p = 0.20$). *beta* = log odds (or logit) coefficient. The addition of a random factor accounting for variance in dropout rates across the 13 study subjects was not significant, hence not needed for adjustment purposes. Variables with *p*-values > .05 were removed in the subsequent model. ^{ns} = not significant, $^{\dagger}p = 0.062$, * = $p < .05$, ** = $p < .01$, *** = $p < .001$. Coefficients may be converted to a probability for dropout as follows: probability = 1 / (1 + exp(−(intercept + $beta_1$*ECTS + $beta_2$*Age + $beta_3$*Gender))). A man who is 22 years would thus have a probability for dropout of 38.4% (given 10 ECTS), 27.1% (given 30 ECTS) or 14.5% (given 60 ECTS).

Discussion

The present study describes system dropout rates and variables that predict staying and dropout rates during students' first study year at one particular Norwegian university. Unexpectedly, weekly study hours and completed number of ECTS were the leading predictors for dropout after one and five years, not study-related variables or GPA.

A unique aspect of the study is the longitudinal follow-up analysis that was possible also five years after enrollment, a time that most of the students would be expected to have completed their degree.

Dropout After the First Year

Maintaining progress during the first year implied a better chance of staying rather than leaving, as also found in another Norwegian study (Hovdhaugen, 2009). Similarly, Bernardo et al. (2016) found that students who persisted simply studied more than students who dropped out (Cohens $d = 0.48$), as confirmed in a recent literature review of dropout conducted by Behr et al. (2020). A multiple number of possible reasons may underlie these findings, e.g. those who study more may follow more functional motivational schedules, have greater confidence in being able to master difficult academic challenges, or have less external burdens like care for other people or paid work that reduces the amount of available time for studying during a week (Behr et al., 2020; Bernardo et al., 2016; Broadbent & Poon, 2015; Richardson et al., 2012). The stayers may also have better study and/or time management skills, as supported by the positive correlation in our data between a strategic learning approach and weekly study hours.

An interesting finding was the quadratic relationship between weekly study hours and dropout, which indicated an accelerated fall in the risk of dropout until flattening out at around 33–35 hours. Whereas this amount of study work seemed optimal, further increases in the number of hours spent studying again started to increase the risk of dropout. However, the most dramatic effect with regard to dropout was evident in the lowest range of time spent studying. It seems fair to conclude that students spending time that roughly corresponds to the normal work week in Norway (37.5 hours) are least likely to quit. Putting in even more study hours may not be effective. This finding mimics research within vocational psychology that has reported a reversed U-curve effect for the relationship between time spent working and performance (Song et al., 2022).

Dropout After the Fifth Year

The longitudinal analysis five years after enrollment, showed that the number of study hours per week during the first year was still a significant predictor, and tentatively for surface approach to learning as well (more surface approach, more dropout). However, after including the academic performance variables, they were replaced by ECTS as the only significant predictor of long-term dropout – an indicator of just getting the job done, however it is done. The number of ECTS has been found to be correlated with individual differences in learning abilities, learning strategies and attention (Gallego et al., 2021), which jointly removes their common contribution from their individual contribution in the understanding of dropout. The reason why ECTS replaces the role of study hours as a five-year dropout predictor may be that first-year students simply need to study hard in order to start earning the ECTS necessary to maintain their opportunity to continue studying. Thereafter, the accumulation of ECTS becomes a more proximal indicator of long-term dropout as compared to time spent studying recorded during the first year.

Null Findings

This study had several unexpected null findings that deserve some attention. They may be connected to the very different curricula trajectories that students may follow after enrollment, thus all types of dropout need not be problematic, as Norwegian universities offer a range of one-year study programs and single subjects that do not award a specific degree. Some students therefore did not intend to achieve such a degree. An additional factor in Norway is that education is free, meaning that anyone satisfying the necessary entry requirements, which may be unrelated to grades or GPA, may enter higher education at no personal cost. This wide-open entrance door is important for securing education for all, but it may also widen the exit door.

In a previous study on the same sample (Sæle et al., 2017), we observed that deep and strategic learning approaches were associated with GPA. In our present study, all learning approaches still correlated with GPA, but not with dropout. Actual time spent studying the first year was more important than the specific learning strategies students use during that time. Hence, we conclude that initially it seems relatively unimportant *how* you study, but more important *that* you study at all! However, since we did, indeed, find correlational relations between student approaches to learning (SAL) and procrastination on the one hand and GPA and study hours on the other, it is possible that an indirect effect is present, where the effect of SAL and procrastination on GPA works through study hours. In our data collection, study hours, SAL and procrastination were measured simultaneously without the possibility to investigate a causal relationship between them, hence we have not tested this hypothesis statistically (i.e. mediation analysis).

Also, while our aim was to shed more light on what distinguishes students who stay and drop out, the majority of the included variables did not have notable predictive value, and those that contributed significantly explained a minor part of the total variance. Variables not included here may have influenced both predictors and the outcome itself.

Another explanation for the null findings may be related to the diverse routes the students chose for their academic journeys. Most students complete the study program they enroll in on time. However, many students are gone for a semester or more, and then they return. Half of the students in our sample changed subject and/or institution during the five-year period. Among the 80.5% that were not characterized as dropouts, only 55% had in fact completed their degree in five years. The final 25% were either still studying – on time, delayed or transferred to another program or institution – or they never intended to complete a degree (seven percent of the students had only enrolled to complete one or more single courses). Finally, ten percent had already completed a degree before enrolling again and entering our data set. This illustrates the difficulties both researchers and universities face when trying to identify dropouts. The picture is complex, and to better understand it, future research might focus on following different subgroups of students to better identify specific predictors and warning flags.

Strengths, Limitations and Further Research

Our access to registry data from DBH, the national data warehouse, gave us the opportunity to follow all participating students for five years, including the ones who migrated away from the institution where the original data were collected. Compared to the difficulties collecting self-report data from students who switch to another program or institution, take a break, or drop out entirely, registry data are less biased and are complete (no missing cells). Still, even though the outcome variable and some of the predictors are based on registry data, several of our most central predictors are based on self-report.

The overall response rate from the entire university population was very low (~9%) despite the use of several reminders, which resulted in a total sample size of 426 students. Given a statistical power of 80%, this sample size may detect Spearman rho correlations > 0.15 and logistic regression odds-ratios > 1.40 for continuous predictors ($M = 0$, SD = 1). The sensitivity for detecting effect sizes in the small-to-medium range was thus adequate; hence, the null findings for procrastination or for learning approaches cannot be explained by an insufficient sample size, except for detecting effect sizes in the smaller range. The potential for missing true effects of at least a moderate size must therefore relate to other factors, e.g. selection biases that may have introduced suppression. A strength was the possibility for comparing demographic differences between participants and non-participants, which showed that more women than men responded but also that the participants were comparable with regard to age. Most importantly, they were also comparable regarding exam grades, thus rejecting the idea that merely hardworking or skilled students responded.

In terms of analytical methods used, Stormark et al. (2008) found that a low response rate primarily biased mean or prevalence estimates, while correlations were less negatively affected. Others have found comparable small non-response biases (Perneger et al., 2005), and simulations show that response rates as low as 5–10% still may yield acceptable reliable estimates (Fosnacht et al., 2017). Nevertheless, the combination of a low response rate and the sampling of students from a single university speaks for caution regarding generalizability, which warrants both a replication and further investigation.

The study-related variables did not contribute at all to the dropout rates after five years. Although we do conclude that time seems to be more important than content when it comes to studying during the first year, the results may also lie in the timing of the questionnaire data collection rather than being a true null finding. These variables were measured during the beginning of the first year, and thus before the students had gathered more comprehensive experiences with what life as a student is all about. The personal journey of developing and fine-tuning their learning approaches, the skill to more effectively regulate tendencies for procrastination and, perhaps, stressors in life in general, might change formidably as the students progress throughout their study career. Other authors have, for instance, found that subject interest decreases during the first year of studying (Bargmann et al., 2022) and that lack of interest also predicts dropout (Bager-Elsborg et al., 2019).

Previous research has found different dropout rates among different subject areas (e.g., Hovdhaugen, 2019). Typically, more students complete professional study programs like nursing and teacher education than in the freer degrees in the humanities and social sciences. In our study, we did not emphasize the importance of the specific subject areas because our aim was to investigate the dropout issue on a diverse sample across different disciplines and programs, not to compare how dropout plays out in the different disciplines. Our sample was also distributed over a broad range of different study programs. However, with a larger sample size, analyzing different patterns across different subjects might still be valuable.

The road from enrollment to graduation may be long and winding, as is often also the case for system dropout (Behr et al., 2020). This is probably one reason for the low explanatory power of the present study. This type of design is limited in its ability to capture dynamic changes over such a long period, and further research should address this. One possible solution is to follow participants more closely and measure variables related to study behavior at several time points during the study program in order to identify changes in such behavior over time.

Conclusions

The results of this study emphasize that just getting students through the first year is important. Action to help students understand their workload and how to manage it should be taken early – as early as during the first semesters (Ortiz-Lozano et al., 2020).

As a friendly note to first-year students who may feel their higher education careers hanging in the balance: Just do it! In your first year of higher education, in the end the fact *that* you study and pass your courses may be more important than *how* you actually study. Dig in, and work more on honing your learning skills once you have settled in.

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