Students' Time Management and Procrastination in the Wake of the Pandemic

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Abstract

On March 12, 2020, Norwegian universities closed campus areas and reorganized teaching to digital environments due to the COVID-19 pandemic. In a sample of 8,907 university students, we investigated how aspects of students' self-regulation were affected by their motivation, perceived stress, working conditions, and remote teaching offered in the new and challenging situation. Specifically, we assumed that self-regulation in terms of time management, procrastination, effort regulation, and time for independent studies might be affected. Analyses based on structural equation modeling (SEM) showed that motivation significantly positively predicted time management and effort regulation and that procrastination negatively predicted time management and effort regulation. Students' perceived stress increased both procrastination and independent study time, whereas remote teaching only weakly reduced procrastination. Students' physical working conditions slightly affected time management. An important finding of the study is the minor impact of students' attendance of remote classes on self-regulation.

Keywords: COVID-19, self-regulated learning, procrastination, higher education

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University campuses are places where students meet professors and fellow peers for learning activities that take place in lecture halls, seminar rooms, laboratories, reading halls, and cafeterias. This unique ecosystem for learning and social activity has been significantly impacted by the COVID-19 outbreak. On March 12, 2020, Norwegian universities closed campus areas and reorganized almost all teaching to digital environments. Students were left with a computer, often in a dorm or living with their parents and siblings. To stay focused on studying despite the changed circumstances and potential distractions in their home environment, students' study activities became more dependent on their willpower and skill at organizing the working day.

Several studies have examined how students and teachers dealt with the new situation during the first three to four months after the introduction of what Bawa (2020) terms *emergency remote teaching* (ERT). Although there is evidence of both teachers and students finding the situation very challenging (Aguilera-Hermida, 2020; Watermeyer et al., 2020), there are also a couple of studies indicating that ERT facilitated students' self-regulation (Bawa, 2020; Gonzalez et al., 2020). For example, Gonzales et al. (2020) found that students engaged in ERT demonstrated better time management skills and performance than students who completed their courses prior to COVID-19. In the study of Bawa (2020), students reported the ERT experience to be generally negative but still performed equal to or higher than students completing courses pre-ERT. These preliminary findings from studies of different ERT environments indicate that the removal of the campus ecosystem does not necessarily imply that students invest less time and effort in their studies. Those studies, however, did not investigate the role of individual differences regarding self-regulation in an ERT environment.

In the present study, we set out to investigate how certain aspects of students' self-regulation together with their working conditions predicted the time and effort invested in study activities during the first months of the COVID-19 lockdown. Based on results from several meta-studies related to self-regulated learning in higher education (Broadbent & Poon, 2015; Credé & Phillips, 2011; Richardson et al., 2012), one could expect students' motivation, time management, and tendency to procrastinate to affect their allocation of time to studying and their invested effort. Furthermore, we expected students' working conditions and class attendance to be of importance. Finally, we expected that a higher level of stress among students could potentially affect their study time and effort.

Self-Regulated Learning and Procrastination

Self-regulated learning (SRL) refers to how learners activate their cognitions, motivations, behaviors, and feelings to reach their goals (Schunk & Greene, 2017). In the present study, we focus specifically on two SRL strategies assumed to capture students' resource management: time management and effort regulation (Pintrich et al., 1993). These two strategies have frequently been demonstrated to relate to achievement measures (e.g., Broadbent & Poon, 2015; Richardson et al., 2012). Time management concerns students' abilities to structure and control their activities, whereas effort regulation involves the degree of students' persistence when facing difficult or boring tasks (Pintrich et al., 1993).

Motivation has been regarded an important part of SRL, and a high level of motivation can potentially impact students' attention, choice of task, and effort (Zimmerman, 2011). The motivational measure Task value indicates students' interest in and perceived worth of a particular task or activity. Task value has been demonstrated to relate to students' self-regulatory processes, specifically to time management and effort regulation (Park & Sperling, 2012; Wolters et al., 2017). In an ERT environment, motivation might be even more important when students engage in study activities.

While task value seems to increase students' SRL, it has been speculated that characteristics of self-regulated learners are more or less lacking in students who frequently procrastinate (Wolters, 2003). In the present study our focus is on the conceptualization of procrastination as "to voluntarily delay an intended course of action despite expecting to be worse off for the delay." (Steel, 2007, p. 66). Several meta-analyses have demonstrated a weak and negative relationship between procrastination and academic performance (Richardson et al., 2012; Steel, 2007). Procrastination also negatively relates to time management and effort regulation in several studies (e.g., Park & Sperling, 2012; Wolters et al., 2017) and to time management in two recent studies conducted during the COVID-19 outbreak (Hong et al., 2021; Pelikan et al., 2021). Likewise, procrastination has been demonstrated to relate negatively to task value (Park & Sperling, 2012; Wolters et al., 2017). These results are not very surprising given that task aversiveness has been demonstrated to trigger procrastination, and that task aversiveness might typically be related to tasks or aspects of the academic environment (Steel, 2007).

The Relevance of Study Time

In several studies, time and effort are overlapping concepts (e.g., Masui et al., 2014; Nonis & Hudson, 2010). We will here distinguish between those two concepts. Effort regulation concerns students' degree of persistence when facing difficult or boring tasks (Pintrich et al., 1993), whereas study time is the number of hours dedicated to studying. The results are mixed on the relationship between study time and achievement in higher education (Doumen et al., 2014; Nonis & Hudson, 2010), probably due to differences in how study time is operationalized and measured (Stinebrickner & Stinebrickner, 2004). Some researchers measure only total study time (e.g., Nonis & Hudson, 2010), while others distinguish between in-class activities and self-study (e.g., Dollinger et al., 2008; Plant et al., 2005). Given that the number of hours used on in-class activities and hours used on self-study appear to be only weakly related (Dollinger et al., 2008; Doumen et al., 2014), we will here differentiate between the two activities when measuring study time.

Results from several studies indicate that study time associated with in-class activities is more strongly related to students' performance than the number of hours spent on self-studying (Credé et al., 2010). However, the context and nature of self-studying should probably be considered. For example, Plant et al. (2005) found that students who studied in a quiet, solitary environment tended to need less time for self-study than those who studied in more disruptive environments. Other studies indicate that study time associated with strategic study approaches was positively related to achievement (Diseth et al., 2010; Valadas, Almeida & Araújo, 2017) and that study time impacted performance when students were able to concentrate and schedule ahead (Nonis & Hudson, 2010). Thus, a positive relationship between time for self-study and achievement seems to depend on students' abilities to self-regulate.

Learning Space and Stress

Although the role of learning space in universities is considered underresearched, there seems to be a growing acceptance that space matters (Ellis & Goodyear, 2016). There are indications that the learning environment might affect students' achievement (Lee et al., 2012), which is in line with results from studies on office occupants in working life (McCoy & Evans, 2005; Vischer, 2008). Prior studies on learning environments have mainly concerned students' perceptions of learning space at the university campus. Regarding informal learning spaces for individual activity, students generally seem to be concerned about noise level, amount of space, light conditions, furniture, and ICT facilities (Cha & Kim, 2015; Cox, 2018). In addition, leisure activities like gaming and TV could more easily compete with students' study activities in the home environment. In a Norwegian national survey conducted approximately seven months after the campus lockdown, 58% of the students reported their working conditions to be not well suited or not at all suited for studying (NOKUT, 2021). Thus, the physical learning environment could be more or less stressful for students in an ERT environment. Studies on how workspace affects office occupants have indicated that workplace stressors can negatively affect biological and psychological processes and that work on complex tasks requiring concentration is most affected (McCoy & Evans, 2005; Vischer, 2008). It seems reasonable that differences in students' perceived learning conditions might be related to aspects of SRL and to stress.

Over the last few years, stress among students in higher education has received increased attention. For example, a national health survey among Norwegian university students conducted at 4-year intervals show 13% increase in mental health problems from 2010 to 2018. In the 2018 survey, 20% of higher education students confirmed that they were often negatively affected by work pressure and concentration difficulties (Sivertsen et al., 2019). Thus, there were already reasons to be concerned about students' experience of stress before COVID-19, and there are indications that students' level of stress have increased in the new ERT context (Loda et al., 2020).

For students, stress in general, and under the COVID-19 situation specifically, can be caused by many factors, such as psychological dispositions, the risk of dropout, decrease in motivation, cognitive and social challenges in the subject that they study and in the learning environment (Robotham, 2008; Sirois et al., 2015). Students' perceived stress has been related to time management issues (Robotham, 2008), procrastination (Sirois, 2014), and effort regulation (Williams et al., 2018). Consequently, it seems reasonable to assume that perceived stress will be related to students' self-regulation and study time in the COVID-19 context.

The Present Study

From one day to another, participants in the present study experienced the university shutdown in March 2020. Except from grocery stores and pharmacies, workplaces and schools were closed. Wherever possible, digital communication became default in worklife and education. In general, students were not able to meet face-to-face due to restrictions on social distancing. Most students and teachers had some experience using digital tools in an educational context, but the sudden transformation to remote teaching was indeed unexpected and teachers and students were mostly unprepared. In the context of social distancing and campus lockdown, students' self-regulation and persistence potentially became more important. Based on our review, we set out to test a structural model capturing how different aspects of students' self-regulation, perceived stress and learning space might affect their effort regulation and study time in an ERT situation.

In line with results from prior studies, we hypothesized that students' task value would relate positively to their time management and effort regulation (Jackson, 2018; Wolters et al., 2017). Likewise, we assumed that task value would be positively related to students' self-study time and the number of hours they attended teaching sessions but negatively related to procrastination. Regarding students' perceived stress and the physical environment, we presumed that those variables would relate negatively to task value.

We expected students' self-reported study time attending organized teaching to be negatively related to procrastination, as teaching hours could provide more structure for self-study. Attending organized activities might imply that students become more dependent on external regulation, and we did not expect to see a significant relationship between organized teaching and students' time management. Based on prior research, we hypothesized that organized study time would be positively, but weakly, related to students' self-study time (Dollinger et al., 2008; Doumen et al., 2014). We also expected that teaching hours could be positively related to effort regulation.

Little is known about how students' physical learning environment might affect aspects of SRL. However, studies on office occupants indicate that workspace affects productivity and performance (Vischer, 2008). Given the specific COVID-19 circumstances, we expected that learning space could be significantly related to both students' effort regulation and to self-study time. Likewise, we expected that learning space could relate to students' perceived stress (McCoy & Evans, 2005). Additionally, we anticipated that a satisfactory learning space would provide more mental resources for time management and fewer excuses to procrastinate.

Based on prior studies, we anticipated that perceived stress would be negatively related to time management and effort regulation (Robotham, 2008; Williams et al., 2018) and positively related to procrastination (Sirois, 2014). However, students might experience stress differently, with some students being motivated by a challenge and others responding negatively (Robotham, 2008). Thus, perceived stress might be positively related to both effort and self-study, as well as to procrastination.

As procrastination could be considered a self-regulatory failure (Steel, 2007), we expected it to relate negatively to both time management, effort regulation, and self-study time. On the other hand, there is reason to believe that time management should be positively related to effort regulation (Jackson, 2018; Park & Sperling, 2012), whereas the relationship between time management and self-study is more of an open question. Nevertheless, we hypothesized that, given the ERT circumstances and fewer institutional scaffolds, students' time management would be more important for their self-study.

Methods

Design and Procedures

The study was a cross-sectional survey and was conducted approximately two months after the university campus was locked down due to the COVID-19 pandemic. An email containing information about the study was distributed to all 25,325 registered full-time students at the eight different faculties at the university. The email stated the purpose of the study, that participation was voluntary, and that participation was anonymous. The email also comprised a link to an electronic questionnaire located at a secure website. The questionnaire contained a short introduction to the study and a written consent. Completed questionnaires were saved anonymously. The management at the university approved the survey.

Participants

A total of 9,490 students responded to the questionnaire, with a response rate of 37.5%. Students more than 40 years old (583) were removed before data was analyzed, constituting a valid sample of 8,907 respondents (M_{Age} = 25.1, SD = 4.4; females: 67.2%, males: 32.2%, non-binary: 0.6%). The sample consisted of students following different study programs, whereof 36.8% of the students enrolled in different bachelor's programs, 52.1% in master's programs, and 11.1% in shorter programs. Compared to the total student population at the university, our sample had approximately the same distribution of students across study programs (BA and MA) and across the different faculties, whereas the number of females were 6.3% higher in the present sample.

Measures

The first part of the survey contained background variables (age, gender, faculty, and study program). For the remaining parts of the survey, the participants were asked to think specifically about the period after the COVID-19 lockdown when responding to the items, and they were reminded to do so before each section of the survey.

Study Time

Single items were used to measure self-organized study time and self-reported participation in class hours (mostly digital). Respondents were asked to assess how many hours per week on average they spent on learning activities after the lockdown. Each question was assessed on an 8-step interval scale ranging from "0-5" to "50 or more".

Physical Study Conditions

Satisfaction with the physical study environment was measured by five items assessing satisfaction with the lighting conditions, the size of the workspace, the computer equipment, the opportunity to study in a quiet place, and the possibility of adjusting chairs and tables. Each item was rated on a seven-step Likert scale ranging from "Very satisfied" to "Dissatisfied". Coefficient alpha (α) in the current sample was .80.

Self-perceived Stress

Self-perceived stress (SPS) was measured by three items. The scale was adapted for the present purpose from previously validated single-item measures of self-perceived stress (e.g., Houdmont et al., 2019). Each item was assessed on a five-point Likert scale with semantic descriptors. Two of the items "How stressful do you find your studies in general?" and "How stressful have you found your studies after March 12" (the date the university closed) were rated by a scale ranging from "Not stressful at all" to "Extremely stressful". The third item "How stressful do you rate your studies compared to others at your age?" was rated from "Much more stressful" to "Much less stressful". The item was reversed before conducting the analyses. Reliability analysis of the three items showed a coefficient alpha (α) of .70.

Procrastination

Subjectively perceived procrastination was measured by the Irrational Procrastination Scale (IPS) (Steel, 2010). The IPS consists of nine statements assessed on a five-point Likert scale, ranging from "Not true of me" to "True of me". Three items, not consistent with increasing procrastination, were reversed before calculating the index. Sample items were "When I should be doing one thing, I will do another" and "I do everything when I believe it needs to be done". The coefficient alpha (α) was .91, which is comparable to the original norm data (Steel, 2010).

Task Value

Motivation for academic work was measured by the "Task Value" subscale from the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al., 1993). Task value provides a measure of the personal interest and importance the student attributes to the subject. Task Value consists of six statements assessed on a ten-point Likert scale, ranging from "Not at all true" to "Very true". Sample items were "I have been very interested in the content area/s of this semester" and "I liked the subject matter of this semester." The coefficient alpha (α) was .92, which is slightly higher than the original norm data (Pintrich et al., 1993).

Time Management

Time management was measured by the "Time and Study Environment Management" subscale from the MSLQ (Pintrich et al., 1993). The subscale provides a measure of how well students perceive their own capability to regulate and manage their time and study environment. The subscale originally consists of eight items assessed on a ten-point Likert scale, ranging from "Not at all true" to "Very true". Sample items were "I make good use of my study time" and "I rarely find time to review my notes or readings before an exam." Three items, not consistent with increasing time management ability, were reversed prior to the analyses. Due to the lockdown, the student had to continue their studies from home. This situation made it difficult to apply regulation strategies to alter or select a suitable study environment. The two items assessing the management of the study environment were consequently no longer considered relevant and therefore omitted from the analysis. The coefficient alpha (α) for the six items was .75, which is comparable to the original norm data (Pintrich et al., 1993).

Effort Regulation

Study effort was measured by the "Effort regulation" subscale from the MSLQ (Pintrich et al., 1993). The subscale provides a measure of how well students perceive their own capability to regulate and manage the intellectual challenges they face when trying to acquire the necessary knowledge and understanding of the subject they are studying. The subscale consists of four items assessed on a ten-point Likert scale, ranging from "Not at all true" to "Very true". Sample items were "I often feel so lazy or bored when I study, that I quit before I finish what I planned to do." and "When course work is difficult, I either give up or only study the easy parts." Two items, not consistent with increasing effort regulation were reversed before the analyses. The coefficient alpha (α) for the four items was .64, which is somewhat lower than the original norm data (Pintrich et al., 1993). As coefficient alpha is highly dependent on the number of items, the mean inter-item correlation was calculated. The result (.31) was within the optimal range, as recommended by Briggs and Cheek (1986).

Statistical Analyses

Descriptives, reliability and bivariate intercorrelations among the study variables were analyzed with IBM SPSS version 26. The structural relationship between the predictor variables and the outcome variables was analyzed in Amos version 26 using structural equation modeling (SEM) with maximum likelihood parameter estimation. As recommended by Kline (2016), the goodness-of-fit of the structural model was evaluated using the model Chi-square (χ^2_{M}), the comparative fit index (CFI), the Root mean square error of approximation (RMSEA), including the 90% confidence interval for RMSEA, and the Standardized Root Mean Square Residual (SRMR). Applying the threshold recommendations by Hu and Bentler (1999), the cutoff criteria for good model fit were CFI >.95, RMSEA<.06, and SRMR <.08. Bootstrap estimation, using bias-corrected 95% confidence intervals, was applied to test the indirect effects (Shrout & Bolger, 2002). The estimates were based on 5,000 bootstrap samples.

In SEM, measurement models and causal relationships among latent constructs are often estimated simultaneously. Confirmatory factor analysis (CFA) makes it possible to examine the relationship between the observed items and the unobserved latent variables (Kline, 2016). As poorly fitted measurement models are prone to influence the fit of the structural model (Williams et al., 2009), CFAs were conducted for scales containing more than three items. As shown in Table 1, the goodness-of-fit values revealed satisfactory fit for procrastination and physical study condition. The goodness-of-fit values for procrastination are within keeping of the values previously reported for this scale (Svartdal et al., 2016). The results for the three subscales selected from the MSLQ revealed that none of the measurement models met the criteria for acceptable fit. RMSEA specifically seems to indicate poor fit.

Table 1.

Goodness-of-fit statistics for confirmatory factor analyses of measurement models.

Variable	$\chi 2$	*df*	CFI	RMSEA	[90% CI]	SRMR
Physical conditions	183.755**	5	.99	.063	.056, .071	.023
Procrastination	1506.512**	27	.97	.078	.075, .082	.034
Task value	2798.961**	9	.93	.187	.181, .192	.042
Time management	982.077**	9	.92	.110	.104, .116	.054
Effort regulation	1290.493**	2	.80	.269	.257, .281	.094

**$p < .01$

Inspecting the items representing each MSLQ subscale indicates that the measured constructs are complex and multidimensional. Pairs of items with highly correlated error terms corroborate this interpretation. Previous psychometric analyses of the MSLQ also point toward a multidimensional structure of the scales (Jackson, 2018). However, the scales were previously validated, well known, and commonly used. Furthermore, there was no intention to examine or modify the properties of the measurement models representing each scale in the current study. Thus, to maintain psychometric rigor and at the same time include measurement error in the analyses of predictors, mediators, and outcome variables, the measurement constructs were modeled as single-indicator latent factors. The advantages and disadvantages of this approach, as well as its use, have been discussed by scholars such as Hayduk and Littvay (2012) and Savalei (2019). The total index score was applied as an observed single indicator. The error variance for each single indicator ($\mathrm{Var}(\epsilon_i)$) was estimated by the formula $[(1-\hat{\rho}_{y_i y_i})\mathrm{var}(y_i)]$ (Bollen, 1989). For the sake of consistency, the large sample size, and because the present reliability estimates were highly comparable with reliability estimates obtained in previous research, reliability estimates from the present study were used when calculating the error variance.

Results

Descriptive Analyses

The results showed weak correlations between the two outcome variables, self-study time (sst) and effort regulation (er), and the background variables gender ($r_{sst,g}$ = .06, $r_{er,g}$ = -.02), age ($r_{sst,a}$ =.01, $r_{er,a}$ =.06), faculty ($r_{sst,f}$ =-.02, $r_{er,f}$ =.01), and study program ($r_{sst,sp}$ = .01, $r_{er,sp}$ =.05). After testing for potential suppressor effects, the background variables were excluded from the main analysis.

Table 2.

Skewness, kurtosis, means, standard deviations and zero-order correlations (r) among study variables.

Variable	*Skew*	*Kurt*	*M*	*SD*	1.	2.	3.	4.	5.	6.	7.
1. Self-study time	.19	-.77	4.05	1.92	–						
2. Teaching hours	1.46	1.94	2.16	1.43	.15**	–					
3. Physical conditions	.11	-.73	3.56	1.51	-.01	-.06**	–				
4. Self-perceived stress	-.19	-.03	3.11	0.78	.16**	.10**	.20**	–			
5. Procrastination	-.17	-.64	3.15	0.90	-.33**	-.17**	.19**	.16**	–		

6. Task value	-.53	-.31	7.06	2.0	.31**	.15**	-.22**	-.11**	-.39**	–		
7. Time management	.11	-.35	5.52	1.84	.34**	.22**	-.26**	-.17**	-.69**	.50**	–	
8. Effort regulation	-.08	-.31	6.06	1.82	.33**	.13**	-.20**	-.11**	-.63**	.42**	.61**	

$^{**}p < .01$

Means, standard deviations, and bivariate correlations (*r*) between all variables included in the analysis are shown in Table 2. Moderate to large zero-order correlations were observed between the variables, except for the association between the physical study environment and self-study time (r = -.01). The strongest relationship (r= -.69) was observed between procrastination and time management. Following the recommendations by Brown (2006), normality, skewness and kurtosis were considered acceptable.

Testing the Theoretical Model

A structural equation model (SEM) was drawn according to the review presented in the introduction. The model contained eight variables, of which two variables (Self-study time and Teaching hours) were modeled as observed constructs. The remaining six variables were modeled as single item latent constructs. Teaching hours, Task value, Physical study environment and Perceived stress were considered exogenous predictors. Procrastination and Time management were drawn as endogenous predictor variables, while Self-study time and Effort regulation were entered as outcome variables. Hypothesized causal paths were drawn between each predictor variable and both outcome variables. Hypothetical paths were also drawn between the exogenous and endogenous predictor variables to represent the assumed indirect effects. Bidirectional paths were drawn between the exogenous predictor variables to accommodate the pattern of covariance often observed between these variables.

Examining the goodness-of-fit of the theoretical model showed a significant chi-square ($\chi2(4) = 176.050$, p < .001), implying that the assumption of exact fit should be rejected. However, considering the large sample size of the present study, a significant Chi-square was expected and therefore not considered critical. The other goodness-of-fit measures showed a satisfactory CFI (.99) and SRMR (.018), while the RMSEA (.069, 90% CI [.061, .078]) indicated a mediocre fit.

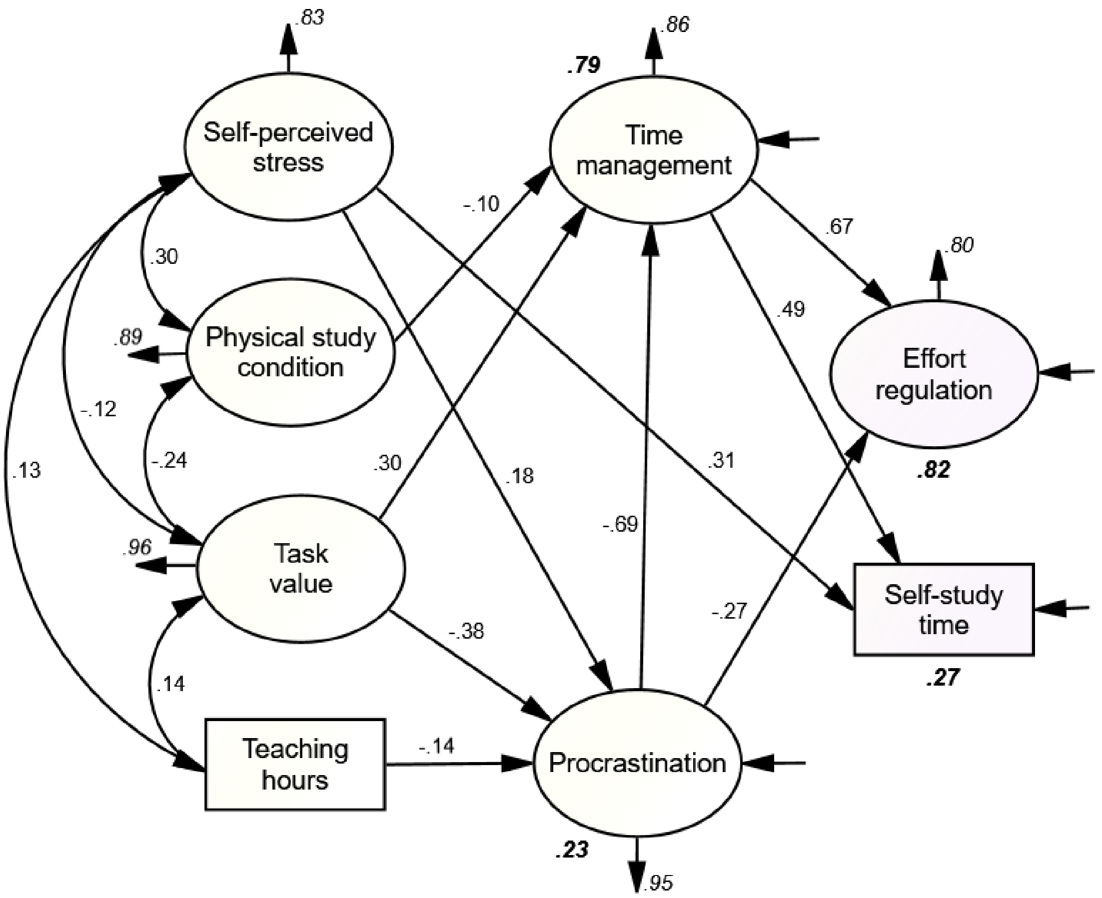
Revising the Model

Inspection of the parameter estimates of the model revealed small, but significant, regression coefficients for several paths. Considering the sample size of the model and its corresponding statistical power, statistical significance was deemed inappropriate as an inclusion criterion. Instead, a model revision was conducted to develop a more parsimonious model with weak paths ($\beta < .10$) constrained to zero. The revision was conducted one path at a time and tested by the Delta chi-square ($\Delta\chi^2$). New paths or covariances were not fitted to the model during this process, making all modified models nested within the theoretical model.

The revised model showed good fit ($\chi2(13) = 406.589$ p < .001), (CFI = .98), (RMSEA = .058, 90% CI [.054, .063]), (SRMR = .027). Due to the large sample size, a significant Chi-square was expected and not considered critical. Comparing the goodness-of-fit statistics for the theoretical model and the revised model revealed a significant chi-square difference ($\Delta\chi2 = 230.539$, $\Delta df = 9$, $p < .001$). This usually implies keeping the theoretical model, as this model contains the fewest parameter restrictions and thereby provides a better explanation of the data. However, the large sample size inflates the statistical power, which implies significant results even with small differences in fit. To test this possibility, the magnitude of the difference in chi-square was calculated using an effect size measure based on Cohen's *w* (Newsom, 2015). The result ($w = .054$) indicates a very small effect of reducing the model. Thus, the difference in chi-square was considered practically unimportant, and the revised, more parsimonious, model was retained. The revised model, explaining 27% of the variance in self-study time and 82% in effort regulation, is presented in Figure 1.

Figure 1.

Final model depicting structural relationships among exogenous predictor variables, endogenous predictor variables, and outcome variables.



Note. The numbers on the arrows are standardized regression coefficients. All depicted regression coefficients were significant at p < .001. Bold italicized numbers are the explained variance in variables. Paths constrained to zero, empirical indicators, and error terms are omitted to enhance readability.

As shown in Figure 1, the two predictors, Self-perceived stress (β = .31) and Time management (β =.49), directly affected Self-study time. Effort regulation was affected directly by Time management (β =.67) and Procrastination (β = -.27). Procrastination was also negatively associated with Time management (β = -.69). High levels of Self-perceived stress were associated with increased procrastination (β =.18). Task value was negatively associated with Procrastination (β = -.38) and positively associated with Time management (β = .30). Physical study conditions and Teaching hours retained only one association each in the revised model. Both variables showed negative associations with Time management (β = -.10) and Procrastination (β = -.14).

Indirect Effects

Several indirect effects were present between the predictor variables and the outcome variables. The indirect effects and their associated 95% confidence intervals are presented in Table 3.

Table 3.

Indirect (mediated) effects and their associated 95% confidence intervals. Unstandardized regression coefficients (b)

	Time management		Effort regulation		Self-study time	
Mediated path	*b*	95% CI Low-High	*b*	95% CI Low-High	*b*	95% CI Low-High
SPS→Pro→ER			-.109	[-.136, -.085]		
SPS→Pro→TM→ER/SST	-.307	[-.353, -.263]	-.190	[-.224, -.158]	-182	[-.212, -.154]
PSC→TM→ER/SST			-.074	[-.089, -.060]	-.071	[-.084, -.058]
TV→TM→ER/SST			.155	[.141, .171]	.149	.138, .162]
TV→Pro→ER			.077	[.061, 093]		
TV→Pro→TM→ER/SST	.216	[.203, .231]	.134	[.120, .149]	.129	[.120, .138]
TH→Pro→ER			.039	[.030, .048]		
TH→Pro→TM→ER/SST	.109	[.093, .125]	.068	[.056, .079]	.065	[.056, .079]
Pro→TM→ER/SST			-.779	[-.853, -.711]	-.748	[-.785, -.712]

Note. SPS= Self-perceived stress, Pro= Procrastination, ER= Effort regulation, SST= Self-study time, PSC= Physical study conditions, TM= Time management, TV= Task value, TH= Teaching hours

High levels of Self-perceived stress seem to predict reduced Effort regulation indirectly by two paths. One path was mediated by Procrastination alone ($\beta = -.05$), and the other path was mediated by both Procrastination and Time management ($\beta = -.08$). High levels of stress were also indirectly associated with reduced Self-study time mediated by a path through Procrastination and Time management ($\beta = -.06$). Reduced satisfaction with the Physical study conditions predicted both reduced Effort regulation ($\beta = -.07$) and Self-study time ($\beta = -.05$) by two paths mediated through Time management. Task value seems to increase Effort regulation and Self-study time by four indirect paths. Two paths were mediated through Time management alone (Effort regulation $\beta = .20$) (Self-study time $\beta = .15$), while two more paths were mediated through both Procrastination and Time management (Effort regulation $\beta = .18$) (Self-study time $\beta = .13$). In addition, Task value affected Effort regulation indirectly through Procrastination alone ($\beta = .10$). Teaching hours were indirectly associated with Effort regulation and Self-study time via three paths. One path, via Procrastination only, indicated increased Effort regulation ($\beta = .04$) with increased Teaching hours. Two additional paths showing the same relationship predicted both Effort regulation ($\beta = .07$) and Self-study time ($\beta = .05$) by paths involving Procrastination and Time management. Finally, Procrastination predicted reduced Effort regulation ($\beta = -.46$) and Self-study time ($\beta = -.34$) by two paths mediated through Time management.

Discussion

The present study presents results from a survey concerning to what extent students' motivation, level of stress, and working conditions affected how they organized their studies and their invested effort when the university campus was closed due to COVID-19. One main contribution of the study is the investigation of relationships between important individual difference variables related to self-regulated learning when ERT is applied. Another contribution is the investigation of how students' perceived stress and the physical environment relate to important aspects of SRL.

Our first hypothesis concerns the role of students' task value, that is, their judgments of how interesting, useful, and important the study content is. We assumed that task value would relate positively to time management, effort regulation, and study time but negatively to procrastination. Our hypothesis was confirmed, except for the relationship between task value and self-study time. Students who valued being engaged in academic tasks also practiced time management and were more persistent than less motivated students, whereas the less motivated students tended to procrastinate more. Those results confirm bivariate correlations demonstrated in prior studies (Park & Sperling, 2012; Wolters et al., 2017), but to our knowledge, they are not confirmed earlier in analyses using structural equation modeling. There was no direct effect of task value on students' self-study time but a weak indirect effect mediated by time management. There was also a weak relationship between task value and students' attendance at digital teaching sessions. These results are in line with studies indicating a relatively weak relationship between students' motivation and study time (Credé et al., 2010). Thus, task value does not seem to be a driving force regarding how much time students invest in their studies but rather affects students' management of and persistence in their study work. Finally, task value correlated negatively with students' perceived level of stress and with their experience of the physical learning environment. While the strength of the relationship between stress and task value is relatively low, there seems to be a somewhat closer negative connection between students' physical working conditions and their motivation. Hence, the learning space students have available in their homes does not seem to stimulate their motivation when that is the only space available.

The number of hours students spent on attending digital teaching sessions negatively predicted procrastination, as hypothesized, but only weakly. In general, digital class attendance did not seem to relate much, or at all, to any of the other variables. This is somewhat surprising, as we assumed that the role of organized digital teaching would increase when students were denied access to the university campus. We note that class attendance has been an important predictor of academic performance in several other studies (e.g., Credé et al., 2010). In a study by Kassarnig et al. (2018), data on social interaction were collected from participants' smartphones, with both location data and digital communication between peers included. An interesting finding was that students' interactions with peers, as indicated by the location data, were an important predictor of academic achievement. Students' opportunities for informal face-to-face discussions and exchange of study-related information outside the lecture hall or seminar room seemed to be important in learning the subjects. Such informal peer interaction is reduced or missing in an ERT environment, and the impact of class attendance might decrease. Some effects of class attendance was indicated in a longitudinal study that took place during the fall 2020, where BA-students to a varying degree were offered on-campus teaching (Fretheim et al., 2021). Results showed positive associations between hours of on-campus teaching on one hand, and students' perceived well-being and teaching satisfaction on the other.

As noted above, students' physical learning space correlated negatively with task value. In addition, increasing dissatisfaction regarding physical working conditions corresponded to higher degrees of perceived stress, with this corroborating findings from studies among office occupants (McCoy & Evans, 2005). In the present situation, it might also be that students' loss of flexibility regarding their learning space is relevant. Before the pandemic, they were able to switch between different places during the day, from reading rooms, computer labs and the library at the university to their working desk at home. The campus lockdown limited their options substantially. However, in contrast to our expectations, students' experience of the physical learning space did not relate to any of the other variables, except that learning space weakly predicted time management.

Students' perceived level of stress did predict their reported number of hours spent on self-studying. The number of hours increased according to how stressful students experienced the situation to be. Hence, one could expect the total number of hours for self-study to increase in the student population, as there are indications that students' level of stress might have increased during the pandemic (Loda et al., 2020). However, students might experience stress differently (Robotham, 2008). In the present study, perceived stress, in line with Sirois (2014), also seems to increase procrastination. Hence, stress seemingly increases some students' self-study, whereas in other cases, stress increases students' tendency to procrastinate.

As hypothesized, procrastination predicted time management and effort regulation negatively, with those results being in accordance with prior studies (e.g., Park & Sperling, 2012; Wolters et al., 2017). Other studies have indicated that those three variables relate to the personality trait conscientiousness, with time management and effort regulation positively and procrastination negatively related to conscientiousness (e.g., Bidjerano & Dai, 2007; Richardson et al., 2012). Conscientiousness is considered to compromise features such as responsibility, the ability to plan, organize and persist (Bidjerano & Dai, 2007). In the current study procrastination has both a medium direct effect on study effort and a medium effect on study effort mediated by time management. Together, procrastination and time management explain a significant part of the variance in effort regulation. Thus, students' persistence in studying despite challenges or being bored can, by and large, be explained by their abilities to plan and monitor their schedule and to avoid temptations to do other things. We assume that those abilities are even more important when external scaffolds are missing. Time management positively predicted both effort regulation and self-study time, whereas procrastination negatively predicted effort regulation. Thus, students' tendency to postpone studying seems primarily related to challenging or boring tasks, while procrastination is not directly related to the total number of hours students invest in self-studying. Procrastinators facing difficult or tiresome study tasks might decide to attend to easier material while still considering themselves to be studying.

Our results show that explained variance in effort regulation is substantially higher than the explained variance in hours used for self-studying, confirming that study time and effort should not be used as overlapping concepts. Effort regulation is intended to measure students' persistence when facing boring or challenging content, whereas the number of self-reported study hours does not indicate the nature of the study activities (Doumen et al., 2014; Plant et al., 2005). The lack of overlap between the two variables is also illustrated in prior studies showing that effort regulation is more strongly related to achievement than self-reported study hours (Broadbent & Poon, 2015; Credé et al., 2010; Richardson et al., 2012). Given that COVID-19 represented a new and more challenging situation for students, one could hypothesize that effort regulation potentially affected achievement even more strongly in the ERT environment.

The current study has several limitations. Among them is the use of a self-report instrument when measuring students' learning behavior. Concerns regarding the validity and reliability of data collected by using such instruments have been discussed in recent decades (e.g., Schellings & Van Hout-Wolters, 2011), and we acknowledge that there are challenges. One argument has been that we cannot be sure of which learning situations the participants have in mind when responding to such instruments. In the current study, we tried to prevent this problem by repeatedly reminding participants to think about the situation after the COVID-19 lockdown when responding to the questions. The measurement of students' study time has also been discussed (e.g., Stinebrickner & Stinebrickner, 2004), and a simple question about the number of hours per week cannot precisely represent students' time spent on studies. More detailed measures, such as logs or diaries, could be suitable for that purpose. However, given the number of participants in the present study, we had to be somewhat pragmatic regarding the measures. The number of females was somewhat higher in the study than in the total student population. Females score higher on the stress variable than males, but controlling for gender did not change relationships between the variables in the model substantially. Finally, we were not able to collect any performance measures in the present study. Although several of the included measures, such as task value, time management, effort regulation and class attendance, have been demonstrated to correlate moderately with performance in prior studies, a performance measure would have strengthened the current study.

Despite the limitations, we believe the outcomes of our study represent important contributions to the understanding of the interrelationship of different aspects of SRL, study time, and some characteristics of remote teaching. First, the results highlight the important role of university students' time-management skills in SRL. Studies in most higher education institutions require more from students regarding their consideration of when, for how long, and under what conditions to engage in academic work. The ERT situation increased the need for students' autonomous time management. Second, students' experience of their home office as their sole physical learning space was related to an increased perceived level of stress and a decreased motivation, but did not affect their persistence or time allocated to studying. It remains to be seen if students' experience of the learning space will affect effort and time used more strongly as the ERT situation continues. Third, attendance at organized teaching sessions only weakly and indirectly, affected students' effort or time for self-study. Although we were not able to analyze whether class attendance was related to performance, our results do seem to deviate from several studies indicating that class attendance significantly predicts performance (Credé et al., 2010). Thus, one could ask if physical attendance is necessary to obtain that positive outcome. In many ways, the pandemic has triggered a new wave of digital mediated teaching in higher education, and one could probably expect post-pandemic university teaching to be affected by tools and designs developed in the time of COVID-19. We believe our results indicate the need to still emphasize on-campus face-to-face interaction, and to carefully consider if students time management skills match new digital solutions. Finally, one should also keep in mind that more screen time might represent more distractions and temptations, with this increasing the potential negative effect of procrastination on students’ persistence and effort regulation.

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