Feeling exhausted and isolated? The connections between university students' remote teaching and learning experiences, motivation, and psychological well-being during the COVID-19 pandemic

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Abstract

We investigated university students' remote teaching and learning experiences, how they connect with psychological well-being, and whether those connections vary depending on motivation. Self-reports were collected from Finnish university students (*N* = 2686). Within the latent variable modeling framework, we classified students according to their expectancy-value-cost profiles, compared latent means, and tested whether the predictions differed across groups. Six groups were identified: *moderately motivated, utility-oriented, disengaged, indifferent, positively ambitious,* and *struggling ambitious*. The groups differed significantly on their experiences and well-being, but predictions were similar across groups: Engagement was predicted positively by evaluation of remote teaching and negatively by perceived strain, exhaustion positively by evaluation of teaching and perceived strain, and depressive symptoms by perceived strain and sense of alienation. Findings suggest that remote teaching and learning experiences during the pandemic contribute to students' well-being in distinct ways, and that certain motivational mindsets might buffer against the negative effects.

Keywords: expectancy-value-cost, psychological well-being, remote teaching, person-oriented, higher education, COVID-19 pandemic

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Introduction

Higher education institutes were forced to make a rapid transition to online teaching and learning due to the COVID-19 pandemic, which drastically influenced both teaching and study practices, and substantially limited students' possibilities to interact with their peers and the academic community. As universities are currently revising and reforming their practices, student support, and even the future of higher education, it is vital to know more about how students experience these immense changes, and what kind of impact those changes have on students' motivation and well-being. In this study, we investigate how Finnish university students experience the transition to remote teaching and learning, how those experiences are moderated by motivation, and how they are associated with psychological well-being.

Despite some generally positive experiences with diverse online learning environments (for reviews, see Ebner & Gegenfurtner, 2019; Means et al., 2013), the unexpected and rapid transition to remote teaching and learning due to the COVID-19 pandemic challenged both teachers and students. Many teachers were unfamiliar with the digital technologies and remote teaching environments, did not manage the pedagogical practices remote teaching requires, had difficulties in converting their courses into an online form, and struggled to maintain interaction and promote peer support (see e.g., König et al., 2020). Concurrently, students were required to adapt quickly to studying more independently, but were lacking the immediate support from face-to-face classes, and many struggled with studying from home (see e.g., Ewing & Cooper, 2021).

Remote teaching and learning also drastically changed the nature of peer interaction due to increased social isolation, thus likely promoting students' sense of alienation from others. Such a negative emotional response to perceived social isolation (Hawkley & Cacioppo, 2010), has been found to be predictive of anxiety, stress, and depression (Richardson et al., 2017). Initial evidence suggests this to be the case during the pandemic as well. Studies among university students have shown an increase in stress and a decrease in mental well-being in the UK (Savage et al., 2020), an increase in students' loneliness, anxiety, and stress in Switzerland (Elmer et al., 2020), and an increase in depressive symptoms in Italy (Meda et al., 2021). However, not all observed consequences have been negative. For example, Elmer et al. (2020) found a decrease in competition among the students, which might be particularly beneficial for those students who do not thrive in a competitive environment. Thus, while the negative impact of the pandemic is undeniable, we should not neglect potential positive experiences either (Lee et al., 2021).

The above implies individual differences in how the drastic changes are perceived and coped with. These differences may be partly due to the variance in individuals' motivational mindsets. For example, in a study on university teachers, Daumiller et al. (2021) found their achievement goals to predict whether the transition to remote teaching was perceived as a positive challenge or threatening. Teachers' learning-focused goals were associated with the view of positive challenge, while performance- and avoidance-focused goals with the view of threat, which, in turn, was also predictive of burnout symptoms. Interestingly, these different views were also translated into student evaluations, so that teachers perceiving the situation as a threat received worse teaching ratings. One implication of this study is that just as teachers, or even more so, also students with different motivational mindsets would seem likely to perceive and experience the transition to remote teaching and learning differently. Thus, the transition could be experienced more positively by students who emphasise high success expectancies and who view their studies as interesting, meaningful, and useful, as these students are more likely to strive for gaining competence. In contrast, the transition could be experienced negatively by students who see studies as costly and express lower expectancies.

Although recent research has demonstrated a change in students' well-being due to the abruptions caused by the pandemic, studies investigating the links between students' subjective experiences of remote teaching and learning and different aspects of well-being are still scarce. Some evidence has, however, emerged suggesting an association between perceived study conditions and depressive symptoms during the COVID-19 pandemic (Matos Fialho et al., 2021).

The transition to remote teaching and learning has also blurred the lines between studying and personal life, which likely results in a stronger interconnection between academic and general well-being. Two widely studied constructs, engagement and emotional exhaustion, represent important positive and negative aspects of academic well-being that are pertinent in the demanding study environment of higher education (Salmela-Aro & Read, 2017). Engagement refers to students' enthusiasm towards, and being absorbed in, studying (Salmela-Aro & Upadyaya, 2012), while exhaustion, one of the core dimensions of burnout, reflects a severe loss of physical and mental energy (Schaufeli et al., 2020). These two constructs have been shown to be negatively associated with each other and linked with important educational outcomes, such as achievement, educational aspirations, and attainment (e.g., Fiorilli et al., 2017; Salmela-Aro & Upadyaya, 2012; Tuominen-Soini et al., 2012; Tuominen-Soini & Salmela-Aro, 2014), and here, taken to reflect both the eagerness and the fatigue experienced in studies during the pandemic.

Depressive symptoms, in contrast, are a significant indicator of a more general psychological well-being, although likely to be connected with academic performance (Hysenbegasi et al., 2005) and motivation (Dykman, 1998; Watt et al., 2019) as well. Depression is characterised by a loss of self-esteem and incentive (Lovibond & Lovibond, 1995), and is relatively strongly associated with social isolation (Elmer & Stadtfeld, 2020). Even though depressive symptoms solely cannot comprehensively reflect students' general well-being, the connections with diminished engagement and elevated exhaustion as well as the combined effect of these constructs on achievement (Fiorilli et al., 2017), and the associations with social isolation, make depressive symptoms particularly relevant in the present context.

Students' well-being is also associated with their motivation (e.g., Tuominen-Soini et al., 2012; Tuominen et al., 2020). This connection is partly inherent in one of the most prominent approaches to student motivation, expectancy-value theory (Eccles et al., 1983; Wigfield & Eccles, 2020), which incorporates three types of motivational constructs. Expectancies refer to subjective beliefs about how well one will succeed, while value can be divided into intrinsic value (the enjoyment derived from an activity or interest in a task), attainment value (personal importance of succeeding in a task), and utility value (perceived usefulness of success in a task). Cost, in contrast, describes the perceived negative consequences of engaging in a task (see Barron & Hulleman, 2015). Recent advancements in the conceptualisation and operationalisation of cost have resulted in facets that resemble measures of well-being. For example, emotional cost has been measured with items referring to perceived exhaustion and stress associated with a subject (e.g., Gaspard et al., 2015). Although it would seem sensible to differentiate cost from well-being, the definition of cost as the complementary counterpart of effort investment nevertheless discloses its motivational relevance, and also suggests that a relative emphasis on the different components of expectancy, value, and cost might result in different motivational configurations with implications for other academic and educational outcomes, including well-being.

Indeed, Watt et al. (2019) identified three expectancy-value-cost profiles, positively engaged (i.e., high on perceived talent, intrinsic and utility values, low on costs), disengaged (i.e., low on perceived talent and intrinsic value, high on utility value and costs), and struggling ambitious (i.e., high on all) that all differently predicted well-being. Struggling ambitious students scored highest on depression, anxiety, and stress, while positively engaged showed the most adaptive well-being. Thus, given the relevance of expectancies, values, and cost in predicting students' commitment, engagement, and performance in academic settings (e.g., Gaspard et al., 2019; Schnettler et al., 2020), as well as its connection with different aspects of student well-being, it would seem reasonable to assume that students with different expectancy-value-cost profiles also differed in how they perceived and experienced the transition to remote teaching and learning, and how it influenced their well-being.

This study aims to enrich current research on expectancy-value-cost motivation in higher education by examining the associations between remote teaching and learning experiences, motivation, and well-being, simultaneously considering a range of expectancy-value-cost dimensions, and by utilising a person-oriented approach to address the relative emphasis of expectancies, values, and costs, and their associations with students' experiences and well-being.

Present Study

This cross-sectional study investigated how differently motivated Finnish university students experienced the transition to remote teaching and learning during the COVID-19 pandemic, and how those experiences were linked with their psychological well-being. As to motivation, we explored the patterning of students' expectancies, values, and costs, as this approach has proven to be particularly informative in showing how acknowledging students' relative emphasis on the different key motivational constructs helps to understand better the connections between motivation and other educationally relevant outcomes. Students' experiences of remote teaching and learning were addressed in terms of how they evaluated the transition to remote teaching (i.e., smoothness of transition, teachers' skills, support for students), how taxing they experienced the transition to be (i.e., mental strain, need for support, difficulties in combining studies and personal life), and how the situation influenced their social connections (i.e., peer support, feeling as an outsider or isolated from others). To gain a more comprehensive understanding of how these experiences contributed to students' well-being, we focused on both positive (engagement) and negative (exhaustion) aspects of academic well-being and general psychological well-being (depressive symptoms). Our research questions were:

(1) What kind of expectancy-value-cost profiles can be identified among university students during the COVID-19 pandemic?

(2) How do the identified profiles differ in terms of remote teaching and learning experiences (i.e., evaluation of remote teaching, strain of remote learning, and sense of alienation) and psychological well-being (i.e., engagement, exhaustion, and depressive symptoms)?

(3) How do university students' remote teaching and learning experiences predict students' concurrent psychological well-being?

(4) Do the associations between remote teaching and learning experiences and well-being vary as a function of students' motivational profiles?

Based on theoretical considerations and prior research (e.g., Perez et al., 2019; Watt et al., 2019), we expected to identify at least three kinds of expectancy-value-cost profiles:

profiles with high values and low costs, profiles with relatively high values and costs, and profiles low on intrinsic value but high on utility value and costs. (*H1*)

We expected the profiles to differ in their remote teaching and learning experiences. Profiles with high values and low costs were expected to show more positive experiences (i.e., higher evaluations of teaching, lower strain and sense of alienation), whereas profiles with both high values and costs were expected to show more mixed experiences (i.e., relatively high evaluations of teaching, but high strain and moderate sense of alienation). Profiles with low intrinsic and high utility and cost were expected to report most negative experiences (i.e., low evaluations of teaching, relatively high strain and sense of alienation). (*H2*)

We further expected the profiles to differ in terms of well-being. Mainly drawing from Watt et al. (2019) and similar studies combining achievement goal and expectancy-value theories (e.g., Tuominen et al., 2020), profiles with high values and low costs were expected to demonstrate the most adaptive well-being (i.e., high engagement, low exhaustion, and low depressive symptoms), profiles with both high values and costs to demonstrate both adaptive and maladaptive well-being (i.e., high engagement but high exhaustion, and depressive symptoms), and profiles with low intrinsic and high utility and cost to demonstrate moderate well-being (i.e., mediocre engagement, mediocre exhaustion, and high depressive symptoms). (*H3*)

Based on a recent study investigating the associations between perceived study conditions and depressive symptoms (Matos Fialho et al., 2021), and some indirect evidence from the available research on students' well-being (e.g., Elmer et al., 2020; Larcombe et al., 2021), during the pandemic, we expected positive evaluations on remote teaching to predict engagement positively, and exhaustion and depressive symptoms negatively, perceived strain of remote learning to predict engagement negatively, and exhaustion and depressive symptoms positively, and sense of alienation to predict exhaustion and depressive symptoms. However, we did not have any grounds to assume the predictions, and hence the processes underlying the expected effects, to vary across the expectancy-value-cost profiles. (*H4*)

Method

Participants and Procedure

Universities in Finland closed their premises and shifted to remote teaching and learning in March 2020, and recommendations to offer only remote teaching in higher education were continued throughout the academic year 2020–2021. Data were collected by online questionnaires in December 2020 – January 2021. Therefore, at the time of the data collection, the students had not participated in face-to-face teaching in 9–10 months.

A total of 2686 university students from three universities in Southern, Western, and Eastern Finland voluntarily participated in the study. On average, the students were 26.45 years old (SD = 7.2), and 75% of them were female, 21% male. Compared to the population, (University Education, 2019), female participants were slightly overrepresented. The students were from different years of university studies (1st = 27%, 2nd = 19%, 3rd = 16%, 4th = 15%, 5th = 12%, 6th or more = 11%) and represented a variety of study fields (e.g., Science = 20%, Arts and humanities = 16%, Educational sciences = 15%, Medical and pharmaceutical sciences = 15%, Social sciences = 13%).

The data collection followed the ethical guidelines of the Finnish National Board on Research Integrity and the University of [masked for blind review] and complied with the GDPR requirements within the EU. All data were handled anonymously and confidentially.

Measures

Expectancy-Value-Cost Motivation

Students' expectancies were measured with three items (e.g., "I expect to do well in my studies") drawn from Bong (2008; also e.g., Jiang et al., 2018). Students' values and costs were assessed by utilising an instrument by Gaspard et al. (2015). Here, we measured intrinsic value (e.g., "I simply like my studies"), importance of achievement (e.g., "Performing well in my studies is important to me") and personal importance (e.g., "The subject matter of my studies is meaningful to me"), utility for job (e.g., "Subject knowledge of my studies will be useful for my future career"), and effort (e.g., "Doing well in my studies requires more effort than I want to put into it") and opportunity (e.g., "To do well in my studies requires that I give up other activities I enjoy") cost facets. Each subfacet was measured with three items on a scale ranging from 1 (not at all true) to 5 (completely true). Confirmatory factor analysis (CFA) on the data showed a good fit after minor modifications (i.e., three pairs of similarly worded items were let to correlate), χ^2 (165) = 1636.574, $p <$ .001, CFI = .950, RMSEA = .057, SRMR = .063.

Remote Teaching and Learning Experiences

The measures for the evaluations of remote teaching and strain of remote learning were drawn from a survey included in a national evaluation of upper secondary students' experiences of remote teaching and learning during the pandemic (The Union of Upper Secondary School Students in Finland, n.d.). The evaluations of remote teaching were measured with three items regarding the smoothness of transition, teachers' skills, and support for students (i.e., "the transition to remote teaching went smoothly", "teachers have had adequate resources to implement remote teaching", and "remote teaching has offered versatile enough support for my study habits", respectively) and the perceived strain of remote learning with three items tapping the mental strain, need for support, and difficulties in combining studies and personal life (i.e., “I find remote teaching and independent studying emotionally taxing”, “I need more support for studying than I am getting”, and “I have difficulties combining studies and the rest of my life”, respectively). Sense of alienation was measured with three items (e.g., “I feel isolated from others”) from the Revised UCLA Loneliness Scale (Russell et al., 1980). The guiding question for perceptions of remote teaching was “All in all, the corona pandemic has caused big changes in how studying has been arranged. What do you think of them?”, and for the associated experiences of strain and sense of alienation “How have you experienced the situation from the point of view of studying?”. The scale ranged from 1 (not at all true) to 5 (completely true).

Psychological Well-Being

To measure different aspects of student well-being, engagement was measured with three items (e.g., “When studying, I am full of energy”) from Schoolwork Engagement Inventory (EDA; Salmela-Aro & Upadyaya, 2012), exhaustion with three items (e.g., “While studying, I feel mentally exhausted”) from the short version of Burnout Assessment Tool (BAT-12; Schaufeli et al., 2020), and depressive symptoms with four items (e.g., “I felt down-hearted and blue”) from the depression subscale of DASS21 (Lovibond & Lovibond, 1995). The scale ranged from 1 (not at all true) to 5 (completely true). A joint CFA on the measures of remote teaching and learning experiences and well-being indicated a good fit to the data after some minor modifications (i.e., error covariances between three pairs of similarly worded items were freed), χ^2 (134) = 1238.277, $p < .001$, CFI = .958, RMSEA = .054, SRMR = .036.

Descriptive statistics and correlations for all variables are shown in Table 1 and factor loadings in the Supplementary Material.

Table 1. Bivariate correlations, descriptive statistics, and internal consistencies for all variables.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. Expectancy	-												
2. Intrinsic	.53**	-											
3. Importance of achievement	.44**	.33**	-										
4. Personal importance	.47**	.75**	.47**	-									
5. Utility for job	.33**	.48**	.30**	.54**	-								
6. Effort cost	-.44**	-.34**	-.07**	-.24**	-.07**	-							
7. Opportunity cost	-.26**	-.20**	.08**	-.09**	-.04	.68**	-						
8. Evaluations of teaching	.18**	.22**	.02	.14**	.10**	-.19**	-.15**	-					
9. Strain of remote learning	-.29**	-.27**	.03	-.14**	-.07**	.42**	.39**	-.59**	-				
10. Sense of alienation	-.23**	-.20**	.06*	-.13**	-.11**	.30**	.29**	-.39**	.60**	-			
11. Engagement	.46**	.66**	.24**	.52**	.31**	-.33**	-.18**	.36**	-.43**	-.30**	-		
12. Exhaustion	-.30**	-.31**	.06*	-.18**	-.08**	.48**	.50**	-.37**	.61**	.47**	-.51**	-	
13. Depressive symptoms	-.35**	-.37**	.00	-.28**	-.20**	.40**	.34**	-.31**	.50**	.52**	-.50**	.62**	-
M	3.70	3.83	4.00	4.14	4.28	3.00	3.02	3.32	3.27	3.13	3.06	3.22	2.35
SD	0.74	0.84	0.81	0.78	0.82	1.03	1.09	1.02	1.20	1.25	0.80	1.05	1.02
α	.70	.85	.88	.79	.93	.83	.87	.75	.81	.86	.81	.88	.89
Skewness	-0.50	-0.60	-0.69	-0.71	-1.32	0.13	0.05	-0.21	-0.36	-0.21	-0.02	-0.08	0.61
Kurtosis	0.33	0.04	0.21	0.48	1.77	-0.72	-0.86	-0.82	-0.96	-1.06	-0.39	-0.86	-0.41

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

Data Analyses

The study combined variable- and person-oriented approaches within the latent variable modeling framework. First, students were classified into distinct motivational groups based on the expectancy-value-cost measures using latent class clustering (LCCA). Then, after ensuring measurement equivalence across the identified motivational profiles, latent means and predictions of remote teaching and learning experiences on well-being were compared between the groups using multi-group structural equation modeling (SEM).

To classify students according to their motivational profiles, we used model-based LCCA, which seeks to identify meaningful patterns representing the mixture of underlying probability distributions in the data, and uses various statistical criteria for deciding the number of classes that fit the data best (Vermunt & Magidson, 2002). For this, we used the Classification Log-likelihood (CL), the Entropy, the Classification Likelihood Criterion (CLC), the Approximate Weight of Evidence (AWE), and a version of the Integrated Classification Likelihood called ICL-BIC, along with standard and entropy R^2, as implemented in the Latent GOLD 5.1 statistics software (Vermunt & Magidson, 2005). CL and Entropy are quantities needed to compute the other three. CLC indicates how well a model performs in terms of fit and classification performance. The AWE and ICL-BIC statistics adds a third dimension to the information criteria described above; they weight fit, parsimony, and the performance of the classification (Vermunt & Magidson, 2016). Generally, the smaller the estimate, the better the fit of the model, except for the indices of R^2, where higher proportion represents better explanation. The classification was followed by a series of ANOVAs to examine group differences on the clustering variables.

In all SEM models, maximum likelihood estimation with robust standard errors estimation (MLR) as implemented in the Mplus statistics software (Muthén & Muthén, 1998-

2017, Version 8.5) was used to obtain robust estimates with missing data. For evaluating model fit, we used the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardised root mean square residual (SRMR) with respective cut-off values of ≥ .90, <.08, and < .08 for adequate fit (Hu & Bentler, 1999), along with the chi-square statistics.

Measurement invariance across the groups was tested in a stepwise manner by increasingly adding restrictions to the model (i.e., configural, metric, scalar, and strict measurement invariance; see, Vandenberg & Lance, 2000). At least partial scalar measurement invariance is a prerequisite for valid comparison of latent means, as it implies the measurement scales to have the same operational definition across groups. Along with evaluating the overall fit of the models, nested models were compared using the likelihood ratio test, and inspecting the degree of change in the fit indices following the recommended cut-off values of ΔCFI (.010), ΔRMSEA (.015), ΔSRMR (.030) for testing metric invariance, and ΔCFI (.010), ΔRMSEA (.015), ΔSRMR (.010) for testing scalar invariance (Chen, 2007).

Given sufficient level of measurement invariance, latent means across the groups were compared by alternately fixing the means of one group to zero and estimating the latent means of the other groups freely. Finally, a structural model was specified where the latent factors representing well-being were regressed on the latent factors representing remote teaching and learning experiences, and the equality of predictive relations across the groups were assessed through imposing restrictions to the structural parameters. Model fit was evaluated as described above.

Results

Expectancy-Value-Cost Profiles

To answer the first research question, we examined what kinds of expectancy-value-cost profiles can be identified among the students. Virtually all statistical criteria from a series of LCCAs supported the six-class solution (see Table 2). As the group sizes were reasonable, and profiles qualitatively informative and theoretically meaningful, we extracted six groups and labelled them according to the mean score profiles: (1) moderately motivated, (2) utility-oriented, (3) disengaged, (4) indifferent, (5) positively ambitious, and (6) struggling ambitious (see Figure 1).

Table 2. Model fit and information criteria values for different cluster solutions.

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9
Entropy R^2	1.00	0.78	0.77	0.77	0.76	0.77	0.75	0.73	0.72
Standard R^2	1.00	0.82	0.77	0.75	0.73	0.72	0.68	0.66	0.62
CL	-29115.28	-27853.16	-27647.81	-27493.65	-27466.30	-27363.50	-27498.86	-27628.73	-27749.01
CLC	58230.56	55706.33	55295.63	54987.29	54932.59	54727.01	54997.72	55257.47	55498.02
AWE	58737.94	56364.03	56103.67	55945.67	56041.30	55986.05	56407.09	56817.17	57208.06
ICL-BIC	58443.75	55982.68	55635.15	55389.98	55398.45	55256.03	55589.90	55912.82	56216.54

Note. CL = classification likelihood, CLC = classification likelihood criterion, AWE = approximate weight of evidence, ICL-BIC = integrated complete likelihood Bayesian information criterion.

The six identified groups differed significantly on all expectancy-value-cost variables with explained variance ranging from 25% to 68% (Table 3). *Moderately motivated* students (25%; N = 658) scored relatively high on expectancy and values and low on costs. *Utility-oriented* students (22%; N = 585) emphasised the utility value and scored relatively high also on personal importance and importance of achievement. This group reported moderate expectancy and intrinsic value, and relatively high costs. *Disengaged* students (16%; *N* = 423) scored relatively low on expectancy and values, and reported rather high costs. *Indifferent* students (15%; *N* = 413) reported moderate expectancy and values, and rather low costs. *Positively ambitious* students (13%; *N* = 356) reported high expectancy and values, and low costs. Finally, *struggling ambitious* students (9%; *N* = 251) reported both high expectancy and values and high costs.

Figure 1. Students' standardised mean scores on expectancy-value-cost scales as a function of group membership.

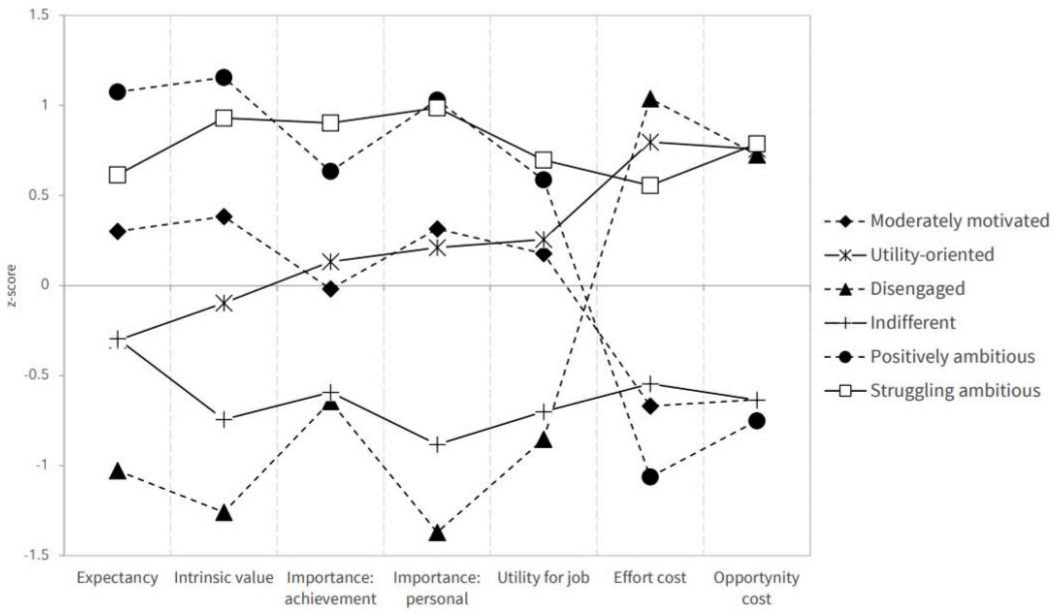


Table 3. Group differences in expectancies, values, and costs.

Variable	Moderately motivated (*N* = 658)		Utility-oriented (*N* = 585)		Disengaged (*N* = 423)		Indifferent (*N* = 413)		Positively ambitious (*N* = 356)		Struggling ambitious (*N* = 251)				
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	$F(5, 2680)$	*p*	η^2
Expectancy	3.93	0.50	3.48_a	0.60	2.95	0.70	3.49_a	0.61	4.50	0.40	4.16	0.54	373.54	< .001	.41
Intrinsic	4.14	0.43	3.75	0.52	2.77	0.68	3.20	0.63	4.79	0.27	4.61	0.36	916.41	< .001	.63
Importance of achievement	3.99	0.68	4.11	0.69	3.48_a	0.84	3.52_a	0.81	4.52	0.54	4.73	0.42	181.70	< .001	.25
Personal importance	4.38	0.32	4.30	0.33	3.07	0.72	3.45	0.61	4.94_a	0.13	4.91_a	0.16	1149.84	< .001	.68
Utility for job	4.43_a	0.61	4.49_a	0.54	3.59_b	1.00	3.71_b	0.82	4.77_c	0.53	4.85_c	0.41	233.51	< .001	.30
Effort cost	2.32_a	0.58	3.82	0.65	4.07	0.59	2.44_a	0.61	1.91	0.58	3.58	0.73	960.58	< .001	.64
Opportunity cost [1]	2.33_a	0.75	3.85_b	0.74	3.82_b	0.84	2.33_a	0.75	2.20_a	0.79	3.89_b	0.78	540.16	< .001	.50

Note. Means within a row sharing the same subscript are not significantly different at the $p < .05$ level (with Games-Howell correction. [1] with Bonferroni correction).

Group Differences in Remote Teaching and Learning Experiences and Psychological Well-Being

Tests of measurement invariance (see Table 4) revealed partial scalar invariance (i.e., two intercepts were estimated freely), thus enabling a valid comparison of latent means across the groups.

Table 4. Measurement invariance across the groups: Fit of alternative models.

Model	Hypothesis	*df*	*χ² MLR*	*CFI*	*RMSEA*	*SRMR*	Comparison	*ΔCFI*	*ΔRMSEA*	*ΔSRMR*	*Δ χ² MLR*	*Δdf*	*p*
M1	Configural	804	1792.14	.953	.052	.045							
M2	Metric	869	1920.59	.950	.052	.052	M2-M1	-.003	.000	.007	127.84	65	<.001
M3	Scalar	934	2398.75	.930	.059	.062	M3-M2	-.020	.007	.010	504.67	65	<.001
M3b	M3 + two intercepts free[1]	924	2098.35	.944	.053	.054	M3b-M2	-.006	.001	.002	181.45	55	<.001
M4	M3b +Equal latent variances	954	2225.36	.939	.055	.070	M4-M3b	-.005	.002	.016	138.81	30	<.001

Note. Although the likelihood ratio tests suggest significant deterioration in some of the models with added constraints, the changes in fit indices remain within the recommended cut-off values (Chen, 2007). [1]Two item intercepts freed: STRAIN1 = "I find remote teaching and independent studying emotionally taxing" and ENG1 = "When studying, I am full of energy."

The results showed positive evaluations of teaching to be rather high in the positively ambitious and moderately motivated students, and lowest in the disengaged group (Table 5 and Figure 2). The utility-oriented and disengaged students scored the highest and positively ambitious the lowest in perceived strain. Sense of alienation was rather high in the utility-oriented, disengaged, and struggling ambitious students, and quite low in moderately motivated and positively ambitious students.

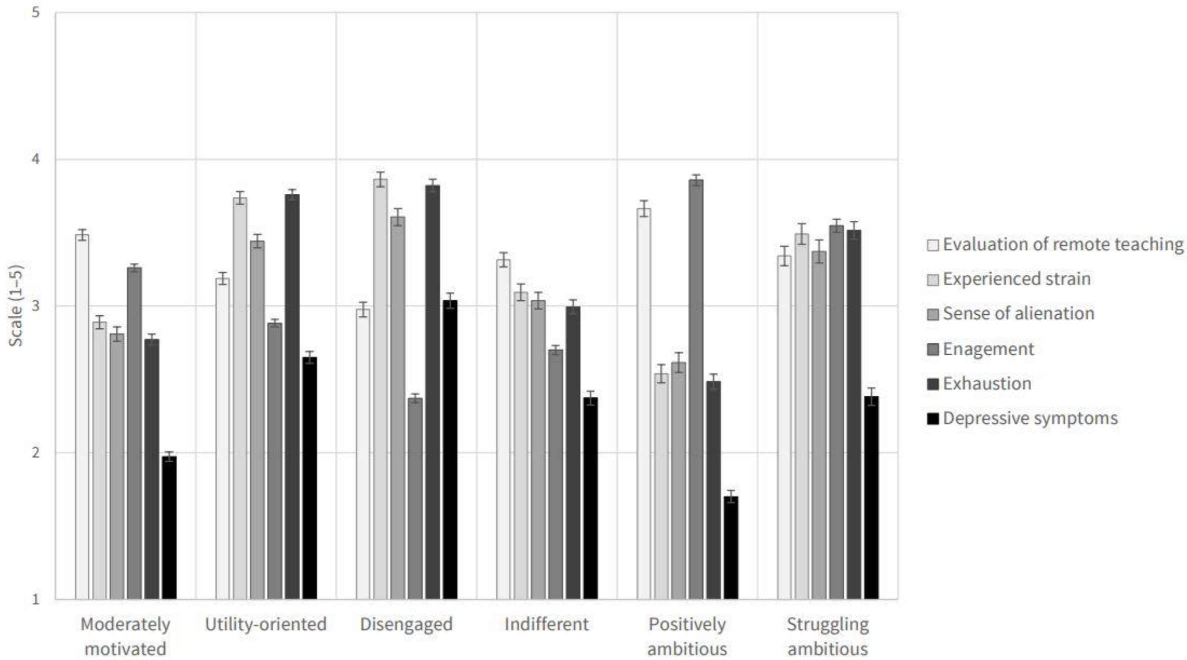
Engagement was highest in the positively ambitious and struggling ambitious students and lowest in the disengaged and indifferent students, whereas exhaustion was highest in the utility-oriented and disengaged groups, and lowest in the positively ambitious and moderately motivated students. The disengaged students also reported the most depressive symptoms, while positively ambitious students the least.

Table 5. Standardised latent mean differences in remote teaching and learning experiences and psychological well-being between expectancy-value-cost groups.

Latent variable	Moderately motivated (N = 658)		Utility-oriented (N = 585)		Disengaged (N = 423)		Indifferent (N = 413)		Positively ambitious (N = 356)		Struggling ambitious (N = 251)	
	M	*S.E.*	*M*	*S.E.*	*M*	*S.E.*	*M*	*S.E.*	*M*	*S.E.*	*M*	*S.E.*
Teach	0.00	.00	-0.36[a]	.07	-0.58	.08	-0.20[a]	.07	0.20	.08	-0.16[a]	.08
Strain	0.00	.00	1.17	.10	1.36	.13	0.30	.08	-0.33	.08	0.82	.11
Alienation	0.00	.00	0.62[a]	.07	0.74	.08	0.22	.07	-0.17	.07	0.46[a]	.09
Engagement	0.00	.00	-0.81	.09	-2.22	.16	-1.34	.11	1.22	.14	0.77	.13
Exhaustion	0.00	.00	1.35[a]	.09	1.43[a]	.10	0.27	.07	-0.33	.08	0.84	.10
Depressive symptoms	0.00	.00	0.80	.06	1.11	.07	0.50[a]	.06	-0.38	.09	0.42[a]	.08

Note. Means within a row sharing the same superscript are not significantly different at the $p \leq .05$ level. Differences in latent means between groups were investigated by comparing each group to a reference group and each group functioned as a reference group. For clarity, only latent means in relation to the first reference group (moderately motivated) are shown.

Figure 2. Students' mean scores in remote teaching and learning experiences and psychological well-being.



Note. For the purposes of illustration, group differences are depicted using composite score means.

Predictive Relations between Remote Teaching and Learning Experiences and Well-Being

To see whether the predictive relations varied between the groups, we constrained the effects to be equal between groups. Since the resulting model fit the data well, χ^2 (999) = 2258.16, $p < .001$, CFI = .940, RMSEA = .053, SRMR = .072, and was no worse than a model with freely estimated predictions, χ^2 (954) = 2197.15, $p < .001$, CFI = .941, RMSEA = .054, SRMR = .062; $\Delta\chi^2$ (45) = 563.62, $p = .035$; ΔCFI = –.001; ΔRMSEA = .001; ΔSRMR = .010, we concluded the predictive relations to be similar across the groups. An inspection of significant effects (Table 6) showed engagement to be positively predicted by evaluations of teaching and negatively by experienced strain, exhaustion to be positively predicted by strain and, interestingly, evaluation of teaching. Depressive symptoms were positively predicted by strain and sense of alienation. The explained variances were around 26% for engagement, 42% for exhaustion, and 33% for depressive symptoms.

Table 6. Standardised effects from remote teaching and learning experiences on well–being.

	Engagement			Exhaustion			Depressive symptoms		
Predictor	*β* (*SE*)	*Z*	*p*	*β* (*SE*)	*Z*	*p*	*β* (*SE*)	*Z*	*p*
Evaluation of remote teaching	.194 (.050)	3.859	<.001	.131 (.046)	2.842	.004	.032 (.043)	0.727	.467
Experienced strain	-.340 (.062)	-5.477	<.001	.716 (.057)	12.625	<.001	.288 (.053)	5.423	<.001
Sense of alienation	-.017 (.037)	-0.454	.650	.042 (.036)	1.149	.250	.359 (.033)	10.921	<.001

Discussion

In this study, we investigated how Finnish university students with different motivational profiles experienced the transition to remote teaching and learning, and how these experiences contributed to students' well-being. Six different motivational profiles were identified that also differed in their remote teaching and learning experiences and well-being. We found that the remote teaching and learning experiences predicted well-being in distinct ways. Yet, the predictive relations were identical across the groups.

Expectancy-Value-Cost Profiles, Remote Teaching and Learning Experiences, and Well-Being

As hypothesised, we identified a group high on values and low on costs (positively ambitious), a group high on both values and costs (struggling ambitious), and a group low on intrinsic value but high on utility value and costs (utility-oriented). Additionally, we found a profile with moderately high values and low costs (moderately motivated), a profile low on values and high on costs (disengaged), and a profile with moderate values and rather low costs (indifferent).

The *positively ambitious* and *struggling ambitious* students both demonstrated high expectancy, and viewed their studies as interesting, meaningful, and useful but differed significantly in their emphasis on costs. The positively ambitious students did not perceive studying as costly and, overall, showed the most adaptive psychological well-being (i.e., high engagement, low exhaustion and depressive symptoms). In contrast, the struggling ambitious students perceived their studies, despite their high values, as energy draining and requiring giving up other activities. Simultaneously feeling engaged and fatigued in studies echoes the findings showing how cost might boost both positive and negative affect in some students (Conley, 2012). The differences between positively ambitious and struggling ambitious students are similar to those found in the Watt et al. (2019) study, where struggling ambitious students, compared to positively engaged students, reported higher costs along with inferior psychological well-being. Also, these findings resemble the differences between mastery- and success-oriented students; the former displaying low costs and adaptive academic well-being, and the latter characterised by elevated costs and high levels of both positive and negative well-being (Tuominen et al., 2020).

Two profiles demonstrated moderate values. The *moderately motivated* and the *utility-oriented* students seemed to consider their studies as rather meaningful and valuable in terms of their future career. However, the moderately motivated found their studies somewhat more interesting, less costly, and felt more efficacious. Similarly as the positively ambitious, the moderately motivated students resembled the positively motivated profile identified by Watt et al. (2019) as these two groups demonstrated similar patterns of motivation, but the moderately motivated showed slightly lower mean levels of expectancies and values and higher costs than the positively ambitious students. Overall, the utility-oriented profile demonstrated more extrinsic motivation, and as expected, felt remote learning as strenuous, similarly to the disengaged group identified by Watt et al. (2019). Consequently, compared to the utility-oriented students, the moderately motivated students reported higher well-being with stronger engagement and lower exhaustion and depressive symptoms.

Both the *indifferent* and *disengaged* students seemed to struggle in finding interest and meaning in their studies. Like previous groups, these profiles differed in costs; compared to indifferent students, who were relatively low on all motivation variables, the disengaged students emphasised high costs, and thus demonstrated overall the most maladaptive motivational pattern. This group resembles the avoidance-oriented profile identified in previous achievement goal orientation research (e.g., Tuominen-Soini et al., 2012; Tuominen et al., 2020), the weakly engaged in engagement research (Korhonen et al., 2017), and the disengaged group in the study by Watt et al. (2019). Consequently, the disengaged group was also high in strain and sense of alienation, which was further reflected in their higher exhaustion and depressive symptoms.

Overall, the identified profiles somewhat overlapped with the profiles identified in previous studies (e.g., Perez et al., 2019; Watt et al., 2019) but there were also some differences. For example, there was higher variation in the raw scores between the profiles in the study by Watt et al. (2019). Similarly as concluded in the study by Perez et al. (2019), university students have been self-selected into their studies and, thus, may be generally more motivated about their studies. Also, it must be taken into account that the variables included in the prior studies have slightly differed and thus the profiles are not directly comparable.

Taken together, the positively ambitious students seemed to have the most adaptive overall profile and the disengaged students the most maladaptive. Cost seemed to be a significant factor as all students, who perceived their studies as costly, seemed to have some unfavourable concomitants of their motivational strivings; whether it was strain and exhaustion experienced by the utility-oriented and the struggling ambitious students, or the alienation, strain, and vulnerability to emotional distress expressed by the disengaged students. For these students, the social aspect of studying may be especially crucial, as they also demonstrated rather high sense of alienation. These findings further demonstrate how the person-oriented approach can enable identifying qualitative differences in students' motivational patterns and their implications (see Niemivirta et al., 2019).

Remote Teaching and Learning Experiences and Students' Well-Being During the Pandemic

Our findings demonstrated the evaluations of remote teaching to be positively predictive of engagement and, interestingly, also exhaustion. That is, a more positive experience of the transition to remote teaching was associated with feeling both energetic and excited, and (although to a lesser extent) mentally and physically weary. Perhaps this is an indication of conscientiousness on the one hand, and commitment on the other hand, thus reflecting a combination of academic pressure and a sense of duty in a new demanding situation. This would be in line with prior findings showing how engaged students with performance concerns are particularly susceptible to emotional exhaustion (e.g., Tuominen et al., 2020).

The perceived strain of remote learning negatively predicted engagement and positively exhaustion and depressive symptoms, suggesting that the increased burden of remote learning significantly affected students' well-being, both in relation to studies and more generally. The particularly strong predictive role of strain may be due to the fact that from the students' viewpoint, the transition to remote teaching and learning was not voluntary but compulsory. Lastly, the sense of alienation was the major predictor of depressive symptoms, which is in line with previous studies demonstrating the importance of social contacts and interaction in higher education (e.g., Richardson et al., 2017; Elmer et al., 2020). During the pandemic, students' social life changed dramatically also outside academia, which may have further accentuated the prevalence and role of the sense of alienation. Given its strong association with the other experiences of remote teaching and learning as well as well-being, social isolation may well be one of the most important factors to attend to when considering and designing new remote teaching practices and environments.

Although the groups with different motivational profiles differed on remote teaching and learning experiences and psychological well-being, the predictions from the experiences on well-being were comparable. This implies that the processes underlying the given effects are similar in all groups during the transition, but that the configuration of different motivational factors moderates its impact on students. For example, the more positive motivational mindsets (e.g., moderate or high expectancy together with high values and low costs) might buffer against the negative changes associated with the transition. Perhaps those holding a more adaptive motivational mind-set may experience the change more as a challenge instead of a threat, as shown in the study by Daumiller et al. (2021) on teachers, which then translates into more positive evaluations and lesser impact on well-being.

Practical Implications

Despite the negative effects of the COVID-19 pandemic, the altered situation can also work as an opportunity to learn more about students' needs in remote teaching and learning, and to improve digital or blended teaching practices. Our findings demonstrate that the way students' experience the changing conditions for learning influences their well-being, and that qualitatively different patterns of motivation play an important role in those experiences. This suggests that when planning and implementing new teaching practices, the awareness of students' diverse motivational mindsets and how they contribute to a variety of study-related experiences would seem particularly beneficial.

The associations between students' sense of alienation and depressive symptoms emphasise the importance of promoting students' sense of belonging and peer support both during the pandemic and also in the post-pandemic times. Also, since viewing studies as costly is related to inferior well-being, it is important to ensure that the academic demands during remote teaching and learning are reasonable and scaled to the given situation, and that sufficient support is available at all times. Emphasising utility more than intrinsic value was accompanied with finding remote learning as taxing and experiencing emotional distress, maybe because remote learning is seen as a hindrance to completing studies. It would seem important to support students in finding intrinsic value in their studies, especially among these students emphasising the utility and more extrinsic outcomes of their studies.

University is a demanding phase in education, and an important social context for students. Thus, it is vital that during the pandemic and even beyond, activities are organised in a way that minimises the loss of social contacts, supports the monitoring of students' motivation and well-being, provides forums for students to engage in on- and off-task interaction, helps to identify students at risk, and allocates human resources targeted at students in need. Although minimising the loss of social contact during remote teaching and learning can be challenging, some significant strategies may be encouraging collaborative and small group working over lone working also in the context of remote studying, and enabling students to connect with each other more freely. It may be valuable to encourage students to be responsive to and supportive of their peers, and during lessons, teachers may consider reserving free time for student interaction by reducing the lesson content to include only the core issues.

Limitations and Future Directions

The study was cross-sectional due to which other types of predictions could be specified as well with equally good model fit. We acknowledge the limitations of using cross-sectional data for such a design but still consider it useful for extracting independent effects of remote teaching and learning experiences on well-being. Hence, we did not argue for strict causal relations between remote teaching experiences and student well-being, but rather considered theoretical justifications, specificity, and time frame when specifying the models (i.e., measures of remote teaching and learning experiences explicitly referred to the transition and reflected factors that were directly influenced by the new situation). Longitudinal data would be needed to better address the likely reciprocal relations over time.

Also, as the measures and their operationalisations were limited to the specific context and followed both the national discourse and already implemented surveys on the theme, we acknowledge that the coverage of remote teaching and learning experiences as well as well-being is limited. A broader set of variables reflecting different aspects and consequences of the exceptional situation would provide a more comprehensive view on its impact on students.

It was necessary to minimise the strain of completing the questionnaire for the participant[1], especially during the demanding time of the pandemic, while still gaining access to valuable information on the students' experiences. Thus, we aimed to choose the most relevant items of each construct based on the previous studies and also in terms of the context. However, we acknowledge that the chosen items cannot fully represent the breadth of the full measures.

Naturally, the generalisation of our findings to other educational systems is limited, as the national guidelines for and implementation of remote teaching vary from country to country, despite the global nature of the pandemic. However, we would expect the findings on the patterning of motivation and its role in different student experiences to have broader relevance, and to provide a good comparison point for similar studies in different educational settings. A related issue is our focus on students' perceptions of the transition to remote teaching and learning instead of the actual practices implemented. Although we consider students' experiences particularly important, especially in connection with motivation and well-being, this perspective would likely benefit from a complementary approach charting the actual pedagogical solutions.

Conclusion

The findings of this study showed that students' experiences of remote teaching and learning during the COVID-19 pandemic were partly dependent on their motivation, but the way those experiences were linked with well-being was not. This implies that some students may be more susceptible to the negative consequences of remote teaching and learning than some others, but that the impact of certain experiences on well-being apply across all students. Consequently, practices to support students and help them cope with the challenging situation could and perhaps should be targeted at both motivation (e.g., promoting intrinsic value and reducing costs) and learning experiences (e.g., reducing strain by recalibrating demands and alleviating social isolation through new ways of interacting formally and informally). Given the disparity of students' experiences, universities should now critically reflect on their policies, and evaluate the purposes and potential of both face-to-face classes as well as remote teaching and learning, in this unprecedented situation and beyond.

Notes

[1] Note, that the survey included several other themes beyond this particular study, due to which it was necessary to optimise the length of the survey. For this, we needed to minimise the number of items in our measures without sacrificing the sufficient conceptual scope of the underlying constructs.

References

Barron, K. E., & Hulleman, C. S. (2015). Expectancy-value-cost model of motivation. *Psychology*, *84*, 261–271. https://doi.org/10.1016/B978-0-08-097086-8.26099-6

Bong, M. (2008). Effects of parent-child relationships and classroom goal structures on motivation, help-seeking avoidance, and cheating. *The Journal of Experimental Education*, *76*(2), 191–217. https://doi.org/10.3200/JEXE.76.2.191-217

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Conley, A. M. (2012). Patterns of motivation beliefs: Combining achievement goal and expectancy-value perspectives. *Journal of Educational Psychology*, *104*(1), 32–47. https://doi.org/10.1037/a0026042

Daumiller, M., Rinas, R., Hein, J., Janke, S., Dickhäuser, O., & Dresel, M. (2021). Shifting from face-to-face to online teaching during COVID-19: The role of university faculty achievement goals for attitudes towards this sudden change, and their relevance for burnout/engagement and student evaluations of teaching quality. *Computers in Human Behavior*, *118*, Article 106677. https://doi.org/10.1016/j.chb.2020.106677

Dykman, B. M. (1998). Integrating cognitive and motivational factors in depression: Initial tests of a goal-orientation approach. *Journal of Personality and Social Psychology*, *74*(1), 139–158. https://doi.org/10.1037/0022-3514.74.1.139

Ebner, C., & Gegenfurtner, A. (2019). Learning and satisfaction in webinar, online, and face-to-face instruction: A meta-analysis. *Frontiers in Education*, *4*. https://doi.org/10.3389/feduc.2019.00092

Eccles, J. S., Adler, T. F., Futterman, R., Goff, S. B., Kaczala, C. M., Meece, J. L., & Midgley, C. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motivation* (pp. 75–146). Freeman.

Elmer, T., Mepham, K., & Stadtfeld, C. (2020). Students under lockdown: Comparisons of students' social networks and mental health before and during the COVID-19 crisis in

Switzerland. *Plos One*, *15*(7), Article e0236337. https://doi.org/10.1371/journal.pone.0236337

Elmer, T., & Stadtfeld, C. (2020). Depressive symptoms are associated with social isolation in face-to-face interaction networks. *Scientific reports*, *10*(1), 1–12. https://doi.org/10.1038/s41598-020-58297-9

Ewing, L. & Cooper, H. B. (2021). Technology-enabled remote learning during COVID-19: Perspectives of Australian teachers, students and parents. *Technology, Pedagogy and Education*. https://doi.org/10.1080/1475939X.2020.1868562

Fiorilli, C., De Stasio, S., Di Chiacchio, C., Pepe, A., & Salmela-Aro, K. (2017). School burnout, depressive symptoms and engagement: Their combined effect on student achievement. *International Journal of Educational Research*, *84*, 1–12. https://doi.org/10.1016/j.ijer.2017.04.001

Gaspard, H., Dicke, A.-L., Flunger, B., Schreier, B., Häfner, I., Trautwein, U., & Nagengast, B. (2015). More value through greater differentiation: Gender differences in value beliefs about math. *Journal of Educational Psychology*, *107*(3), 663–677. https://doi.org/10.1037/edu0000003

Gaspard, H., Wille, E., Wormington, S. V., & Hulleman, C. S. (2019). How are upper secondary school students' expectancy-value profiles associated with achievement and university STEM major? A cross-domain comparison. *Contemporary Educational Psychology*, *58*, 149–162. https://doi.org/10.1016/j.cedpsych.2019.02.005

Hawkley, L. C., & Cacioppo, J. T. (2010). Loneliness matters: A theoretical and empirical review of consequences and mechanisms. *Annals of Behavioral Medicine*, *40*(2), 218–227. https://doi.org/10.1007/s12160-010-9210-8

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: a Multidisciplinary Journal*, *6*(1), 1-55. https://doi.org/10.1080/10705519909540118

Hysenbegasi, A., Hass, S. L., & Rowland, C. R. (2005). The impact of depression on the academic productivity of university students. *The Journal of Mental Health Policy and Economics, 8*(3), 145–151.

Jiang, Y., Rosenzweig, E. Q., & Gaspard, H. (2018). An expectancy-value-cost approach in predicting adolescent students' academic motivation and achievement. *Contemporary Educational Psychology*, *54*, 139–152. https://doi.org/10.1016/j.cedpsych.2018.06.005

König, J., Jäger-Biela, D. J., & Glutsch, N. (2020). Adapting to online teaching during COVID-19 school closure: Teacher education and teacher competence effects among early career teachers in Germany. *European Journal of Teacher Education*, *43*(4), 608–622. https://doi.org/10.1080/02619768.2020.1809650

Korhonen, V., Inkinen, M., Mattsson, M., & Toom, A. (2017). Student engagement and the transition from the first to second year in higher education. In E. Kyndt, V. Donche, K. Trigwell, & S. Lindblom-Ylänne (Eds.), *Higher Education Transitions: Theory and Research* (pp. 113-134). Routledge - Taylor & Francis Group.

Larcombe, W., Baik, C., & Finch, S. (2021). Exploring course experiences that predict psychological distress and mental wellbeing in Australian undergraduate and graduate coursework students. *Higher Education Research & Development*, 1–16. https://doi.org/10.1080/07294360.2020.1865284

Lee, K., Fanguy, M., Lu, X. S., & Bligh, B. (2021). Student learning during COVID-19: It was not as bad as we feared. *Distance Education*, *42*(1), 164–172. https://doi.org/10.1080/01587919.2020.1869529

Lovibond, P. F., & Lovibond, S. H. (1995). The structure of negative emotional states: Comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. *Behaviour Research and Therapy*, *33*(3), 335–343. https://doi.org/10.1016/0005-7967(94)00075-U

Matos Fialho, P. M., Spatafora, F., Kühne, L., Busse, H., Helmer, S. M., Zeeb, H., Stock, C., Wendt, C., & Pischke, C. R. (2021). Perceptions of study conditions and depressive symptoms during the COVID-19 pandemic among university students in Germany: Results of the international COVID-19 student well-being study. Frontiers in Public Health, 9, Article 674665. https://doi.org/10.3389/fpubh.2021.674665

Means, B., Toyama, Y., Murphy, R., & Baki, M. (2013). The effectiveness of online and blended learning: A meta-analysis of the empirical literature. *Teachers College Record*, *115*(3), 1–47.

Meda, N., Pardini, S., Slongo, I., Bodini, L., Zordan, M. A., Rigobello, P., Visioli, F., & Novara, C. (2021). Students' mental health problems before, during, and after COVID-19 lockdown in Italy. *Journal of Psychiatric Research*, *134*, 69–77. https://doi.org/10.1016/j.jpsychires.2020.12.045

Muthén, L. K. & Muthén, B. O. (1998–2017). *Mplus User's Guide*. Eighth Edition. Muthén & Muthén.

Niemivirta, M., Pulkka, A.-T., Tapola, A., & Tuominen, H. (2019). Achievement goal orientations: A person-oriented approach. In K. A. Renninger, & S. E. Hidi (Eds.), *The Cambridge handbook of motivation and learning* (pp. 566–616). Cambridge University Press.

University Education (2019, May 9). *Official Statistics of Finland.* Retrieved May 27, 2021, from http://www.stat.fi/til/yop/2018/yop_2018_2019-05-09_tie_001_en.html

Perez, T., Wormington, S. V., Barger, M. M., Schwartz-Bloom, R. D., Lee, Y., & Linnenbrink-Garcia, L. (2019). Science expectancy, value, and cost profiles and their proximal and distal relations to undergraduate science, technology, engineering, and math persistence. *Science Education*, *103*(2), 264–286. https://doi.org/10.1002/sce.21490

Richardson, T., Elliott, P., Roberts, R., & Jansen, M. (2017). A longitudinal study of financial difficulties and mental health in a national sample of British undergraduate students. *Community Mental Health Journal*, *53*(3), 344–352. https://doi.org/10.1007/s10597-016-0052-0

Russell, D., Peplau, L. A., & Cutrona, C. E. (1980). The revised UCLA Loneliness Scale: Concurrent and discriminant validity evidence. *Journal of Personality and Social Psychology*, *39*(3), 472–480. https://doi.org/10.1037/0022-3514.39.3.472

Salmela-Aro, K., & Read, S. (2017). Study engagement and burnout profiles among Finnish higher education students. *Burnout Research*, *7*, 21–28. https://doi.org/10.1016/j.burn.2017.11.001

Salmela-Aro, K., & Upadaya, K. (2012). The Schoolwork Engagement Inventory: Energy, Dedication, and Absorption (EDA). *European Journal of Psychological Assessment*, 28(1), 60–67. https://doi.org/10.1027/1015-5759/a000091

Savage, M. J., James, R., Magistro, D., Donaldson, J., Healy, L. C., Nevill, M., & Hennis, P. J. (2020). Mental health and movement behaviour during the COVID-19 pandemic in UK university students: Prospective cohort study. *Mental Health and Physical Activity*, *19*, Article 100357. https://doi.org/10.1016/j.mhpa.2020.100357

Schaufeli, W. B., Desart, S., & De Witte, H. (2020). Burnout Assessment Tool (BAT)—Development, validity, and reliability. *International Journal of Environmental Research and Public Health*, *17*(24), Article 9495. https://doi.org/10.3390/ijerph17249495

Schnettler, T., Bobe, J., Scheunemann, A., Fries, S., & Grunschel, C. (2020). Is it still worth it? Applying expectancy-value theory to investigate the intraindividual motivational process of forming intentions to drop out from university. *Motivation and Emotion*, *44*, 491–507. https://doi.org/10.1007%2Fs11031-020-09822-w

The Union of Upper Secondary School Students in Finland. (n.d.). *Lukiolasten koronakyselyn tulokset [Results of the upper secondary school students' Covid-19 -survey]*. Retrieved May 24, 2021, from https://lukio.fi/app/uploads/2020/04/Lukiolaisten-koronakyselyn-tulokset.pdf

Tuominen, H., Juntunen, H., & Niemivirta, M. (2020). Striving for success but at what cost? Subject-specific achievement goal orientation profiles, perceived cost, and academic well-being. *Frontiers in Psychology*, *11*, Article 557445. https://doi.org/10.3389/fpsyg.2020.557445

Tuominen-Soini, H., & Salmela-Aro, K. (2014). Schoolwork engagement and burnout among Finnish high school students and young adults: Profiles, progressions, and educational outcomes. *Developmental Psychology*, *50*(3), 649–662. https://doi.org/10.1037/a0033898

Tuominen-Soini, H., Salmela-Aro, K., & Niemivirta, M. (2012). Achievement goal orientations and academic well-being across the transition to upper secondary education. *Learning and Individual Differences*, *22*, 290–305. https://doi.org/10.1016/j.lindif.2012.01.002

Vandenberg, R. J., & Lance, C. E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods*, *3*(1), 4–70. https://doi.org/10.1177/109442810031002

Vermunt, J. K., & Magidson, J. (2002). Latent class cluster analysis. In J. A. Hagenaars, & A. L. McCutcheon (Eds.), *Applied Latent Class Analysis* (1st ed., pp. 89–106). Cambridge University Press. https://doi.org/10.1017/CBO9780511499531.004

Vermunt, J. K., & Magidson, J. (2005). *Technical Guide for latent Gold Choice 4.0: Basic and Advanced.* Statistical Innovations Inc.

Vermunt, J. K., & Magidson, J. (2016). *Upgrade manual for Latent GOLD 5.1*. Statistical Innovations Inc.

Watt, H. M. G., Bucich, M., & Dacosta, L. (2019). Adolescents' motivational profiles in mathematics and science: Associations with achievement striving, career aspirations and psychological wellbeing. *Frontiers in Psychology*, *10*, Article 990. https://doi.org/10.3389/fpsyg.2019.00990

Wigfield, A., & Eccles, J. S. (2020). 35 years of research on students' subjective task values and motivation: A look back and a look forward. *Advances in Motivation Science*, *7,* 161–198. https://doi.org/10.1016/bs.adms.2019.05.002

Supplementary Material

1 Confirmatory Factor Analyses: Factor Loadings and Residual Variances

Table S1: Standardised Factor Loadings and Residual Variances for the Chosen Measurement Model for Expectancies, Values, and Costs.

	Factor loadings							
Item	EXP	INT	IOA	PI	UTI	EFF	OPP	Residual variances
EXP1	.84							.30
EXP2[1]	.47							.78
EXP3[1]	.45							.80
INT1[2]		.72						.49
INT2[2]		.87						.24
INT3[3]		.78						.39
IOA1			.88					.23
IOA2			.89					.21
IOA3			.78					.39
PI1[3]				.76				.42
PI2				.76				.43
PI3				.71				.49
UTI1					.88			.23
UTI2					.92			.15
UTI3					.91			.18
EFF1						.65		.58
EFF2						.80		.36
EFF3						.89		.20
OPP1							.82	.33
OPP2							.91	.18
OPP3							.77	.41

Note. EXP = expectancies; INT = intrinsic value; IOA = importance of achievement; PI = personal importance; UTI = utility for job; EFF = effort cost; OPP = opportunity cost. Error covariances between three pairs of similarly worded items were freed: [1]Items EXP2 “I know that I will be able to learn the material for my studies" and EXP3 “I am sure I can do an excellent job on the problems and tasks assigned for my studies”; items INT1 “Studying is fun for me” and INT2 “I simply like my studies”; and items INT3 “The subject matter of my studies interests me” and PI1 “The subject matter of my studies is meaningful to me.”

Table S2: Standardised Factor Loadings and Residual Variances for the Chosen Measurement Model for Remote Teaching and Learning Experiences and Psychological Well-Being.

	Factor loadings						
Item	TEACH	STRAIN	ALIEN	ENG	EXH	DEP	Residual variances
TEACH1	.73						.47
TEACH2	.55						.70
TEACH3[1]	.80						.37
STRAIN1[1]		.76					.42
STRAIN2		.80					.36
STRAIN3		.72					.48
ALIEN1			.78				.40
ALIEN2			.86				.27
ALIEN3			.83				.32
ENG1				.89			.21
ENG2[2]				.76			.43
ENG3[2]				.56			.69
EXH1					.88		.22
EXH2					.82		.34
EXH3					.81		.35
DEP1						.84	.30
DEP2[3]						.84	.30
DEP3[3]						.72	.49
DEP4						.82	.33

Note. TEACH = experiences of remote teaching; STRAIN = strain of remote learning; ALIEN = sense of alienation; ENG = engagement; EXH = exhaustion; DEP = depressive symptoms. Error covariances between three pairs of items were freed: [1]Items TEACH3 “Remote teaching has offered versatile enough support for my study habits” and STRAIN1 “I find remote teaching and independent studying emotionally taxing”; items ENG2 “I am enthusiastic about my studies” and ENG3 “I am really involved in my studies”; and items DEP2 “I feel down-hearted and blue” and DEP3 “I feel I wasn't worth much as a person.”