University students' profiles of burnout symptoms amid the COVID-19 pandemic in Germany and their relation to concurrent study behavior and experiences

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ABSTRACT

Burnout symptoms are prevalent among university students. This study examined students' understudied profiles of burnout symptoms and their relation to procrastination, dropout intentions, and study- and life satisfaction. We used cross-sectional data from two online-studies conducted in Germany in April 2020 amid the COVID-19 pandemic (N_{study1} = 597, N_{study2} = 857). Latent profile analyses indicated three profiles in both studies: (1) *well-functioning*, (2) *moderately exhausted-inefficacious*, and (3) *burned-out*. Most students belonged to Profiles 1 and 2 with low to moderate burnout symptoms. Students in Profile 3 reported the highest symptoms, most procrastination, strongest dropout intentions, and lowest study- and life satisfaction. The distinct profiles broaden knowledge about intra-individual differences in students' burnout experiences and underpin the need for tailored interventions.

1. Introduction

Successfully graduating from university bears several benefits for students (e.g., advanced skills and employment opportunities; Baum et al., 2013). On the road to academic success, however, several students struggle preserving through challenges and experience burnout symptoms (Grützmacher et al., 2018). Globally, researchers cautioned about these symptoms given their associations with dysfunctional study behavior (Balkis, 2013) and adverse academic- and health-related experiences (Kristinato et al., 2016; Madigan & Curran, 2020). Schaufeli et al. (2002) posited that student burnout is a multidimensional phenomenon that comprises three distinct symptoms: *emotional exhaustion* due to extensive study demands, *cynicism* referring to detached attitudes toward one's studies, and *reduced professional efficacy* describing a reduced confidence in one's academic-related competencies and abilities.

Tenets of theoretical models (Demerouti et al., 2001; Leiter & Maslach, 1988) postulate that burnout symptoms emerge insidiously

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and sequentially over time due to incessant demands (e.g., a massive workload) and an enduring resource depletion (e.g., external support). Since the demands and resources of students typically differ, variations in their susceptibility to and patterns (i.e., latent profiles) of burnout symptoms are also likely. The examination of students' unique profiles is indispensable to obtain fine-grained insights into their specific experiences, challenges, and needs (cf. Leiter & Maslach, 2016). Person-oriented statistical methods are well-suited to gain such insights. Besides, these methods can extend the inconclusive knowledge about the multidimensionality of student burnout by unraveling how the respective symptoms interplay on an intra-individual level. Nonetheless, person-oriented methods received limited attention in burnout research so far (Mäkikangas & Kinnunen, 2016). Portoghese et al. (2018) and Salmela-Aro and Read (2017) shed initial light on profiles of burnout symptoms among Finnish and Italian university students. Empirical evidence on such profiles among students from other countries is nonexistent, limiting the generalizability of prior findings. Scarce evidence also exists on how such profiles relate to students' sociodemographic characteristics and concurrent study behavior and academic- and health-related experiences. Yet, these insights can provide a more differentiated and holistic view of the profiles and their specific challenges and needs.

Accordingly, the current cross-sectional research had three overarching goals. First, we examined whether *university students in Germany* showed similar profiles of burnout symptoms as previously identified in the Finnish and Italian higher education contexts (Portoghese et al., 2018; Salmela-Aro & Read, 2017). To this end, we adopted a person-oriented approach and analyzed cross-sectional data from two distinct studies during the COVID-19 pandemic. Second, we investigated whether particular sociodemographic characteristics of students predicted their membership in a specific profile. Such insights are nonexistent so far although supportive for identifying student groups that seem at higher risk of experiencing more pronounced symptom levels. Third, we provided first evidence on how the identified profiles differed concerning other variables, namely academic procrastination, university dropout intentions, and study- and life satisfaction. These variables showed associations with student burnout symptoms in prior studies (Atalayin et al., 2015; Balkis, 2013; Cazan et al., 2015; Mostert & Pienaar, 2020) and reflect strong predictors of academic success (Antaramian, 2017; Faas et al., 2018; Goroshit, 2018; Peixoto et al., 2021; Scheunemann et al., 2021). Thereby, we provided a more differentiated understanding of the association between burnout symptoms and the other variables and a more thorough picture of the profiles, which is paramount for designing effective interventions.

2. Literature review

Empirical findings indicated that students encounter an array of challenges in the higher education context (e.g., extensive workload, impaired academic performance, financial burden, and time pressure; Stallman & Hurst, 2016). Cross-national studies revealed that around a third of students have difficulties in managing these challenges and consequently suffer detrimental mental health issues (Auerbach et al., 2018), particularly those related to anxiety, depression, and substance use (see also Rotenstein et al., 2016). Since the outbreak of COVID-19 in 2020, researchers found an increase in prevalence and exacerbations of such mental health issues in students (Elmer et al., 2020; Ochnik et al., 2021). This alarming development is no surprise considering that the COVID-19 pandemic necessitated unprecedented containment measures and created additional novel challenges for students (e.g., curfews, quarantines; restrictions on social interaction, and switch to online learning; Browning et al., 2021).

Challenges in the higher education context make students also susceptible to symptoms of burnout (cf. Hobfoll, 1989; Kaggwa et al., 2021). Salmela-Aro et al. (2022) recently indicated that prevalence rates of these symptoms increased since the COVID-19 outbreak. To assess student burnout symptoms, most empirical research used the prominent Maslach Burnout Inventory Student-Survey (MBI-SS; Schaufeli et al., 2002). The MBI-SS assumes that three distinct symptoms underly the concept of student burnout, namely *emotional exhaustion* (tiredness and depletion due to extensive study demands), *cynicism* (detached attitudes toward one's study), and *reduced professional efficacy* (reduced confidence and belief in one's academic-related competencies and abilities). So far, no agreement exists on whether reduced professional efficacy is integral to burnout (De Beer et al., 2020). In particular, this disagreement is attributable to occupational studies that identified reduced professional efficacy to weakly associate with exhaustion and cynicism (Mäkikangas & Kinnunen, 2016). This identification triggered the conclusion in research on burnout that exhaustion and cynicism denote the core and only burnout symptoms. However, a weak correlation does not necessarily rule out that reduced professional efficacy is part of burnout. Possibly, the onset of this symptom did not yet begin at the time of assessment. The developmental burnout process model (Leiter & Maslach, 1988) undermines this assumption. This model suggests that burnout symptoms unfold in a specific sequential order: exhaustion unfolds in the primary stage, cynicism emerges next, and reduced professional efficacy manifests last. Contrary, however, the model by Golembiewski (1986) postulates that exhaustion develops in the last stage. So far, theoretical models to elucidate the developmental order of burnout symptoms *among students* per se are nonexistent.

The *Diagnostic and Statistical Manual of Mental Disorders* (5th ed.; *DSM-5*; American Psychiatric Association, 2013) does not classify and include burnout as a mental disorder, which should not undermine the adverse consequences of this phenomenon for students. Indeed, empirical research identified associations between student burnout and various mental health issues such as depression (Galán et al., 2014), eating disorders (Kristinato et al., 2016), and alcohol abuse (Jackson et al., 2016). In addition, prior research identified these symptoms to associate with adverse academic experiences such as academic procrastination (Balkis, 2013), impaired academic achievement (Madigan & Curran, 2020), university dropout intentions (Mostert & Pienaar, 2020), and reduced study- and life satisfaction (Atalayin et al., 2015; Cazan et al., 2015). Empirical studies identified those experiences as strong predictors of academic success (Antaramian, 2017; Faas et al., 2018; Goroshit, 2018; Peixoto et al., 2021; Scheunemann, 2021). Amongst other things, the current study puts a focus on these experiences (to provide first evidence on how profiles of burnout symptoms differ in these experiences).

Until now, most researchers examined the antecedents of student burnout symptoms (e.g., Gusy et al., 2016; Sveinsdóttir et al.,

2021). To this end, they applied different theoretical frameworks, of which the Conservation of Resources (COR) Theory (Hobfoll, 1989) and the Job Demands-Resources (JD-R) Model (Demerouti et al., 2001) are the most prominent in this research context. These two models consistently postulate that burnout symptoms can emanate gradually over time because of successive demand accumulation and resource loss. Empirical findings supported this theoretical postulation (Gusy et al., 2016; Lesener et al., 2020). Since the availability of resources and presence of demands typically differ among students, variations in their vulnerability to and patterns of burnout symptoms are conceivable.

Leiter and Maslach (2016) elucidated that different patterns of burnout symptoms are also expectable since these symptoms address interrelated but distinct aspects of individuals' experiences. To examine how burnout symptoms are organized within individuals, person-oriented statistical methods are well-suited. Compared to variable-oriented methods (e.g., structural equation modeling) that focus on associations between variables, person-oriented statistical methods (e.g., profile analyses) aim to identify hidden homogenous subgroups (i.e., groups that share similar patterns of responses on studied phenomena) within a heterogeneous population (Ferguson et al., 2020). So far, most empirical studies on burnout applied variables-oriented methods that should be increasingly supplemented by person-oriented methods because of their manifold advantages (Laursen & Hoff, 2006; Mäkikangas & Kinnunen, 2016).

To date, empirical studies on patterns (i.e., latent profiles) of burnout symptoms in students are scarce and revealed different profiles solutions (three- and four-profile solutions; Portoghese et al., 2018; Salmela-Aro & Read, 2017). Sources for this inconsistency in profile solutions could be that the authors used slightly different measures of the three burnout symptoms (exhaustion, cynicism, and reduced professional efficacy/inadequacy), wherefore these solutions warrant careful comparison. In brief, Portoghese et al. (2018) and Salmela-Aro and Read (2017) similarly identified *burned-out profiles* with high scores on all symptoms and *engaged profiles* with low scores on all symptoms. In addition, Portoghese et al. (2018) identified an *overextended profile* with high exhaustion, and moderate cynicism and professional efficacy. Salmela-Aro and Read (2017) further identified an *inefficacious profile* (moderate exhaustion, and high cynicism and inadequacy) and an *engaged-exhausted profile* (moderate exhaustion, low cynicism, and moderate inadequacy). Cynicism is surprisingly the least pronounced symptom in the engaged-exhausted profile, perhaps because it develops in the last stage of the burnout process (i.e., after the other two burnout symptoms manifest) and reflects the final straw that breaks the camel's back. In this case, the developmental burnout process model of Leiter and Maslach (1988) and the model of Golembiewski (1986) would not apply to students as neither of these theoretical perspectives assume that cynicism unfolds last.

Comparing students' profiles of burnout symptoms concerning other studied variables can provide a more thorough knowledge about the profiles and their respective challenges. Person-oriented statistical methods are also well-suited to make such comparisons. Salmela-Aro and Read (2017) provided initial evidence in this regard, indicating that students in the profiles with the most pronounced burnout symptoms had been studying the longest and concurrently experienced lower resources (suitedness to study field, social support), higher demands (internet dependency, loneliness), and higher depression. Considering previous variable-oriented studies, it seems conceivable that these students also differed in their sociodemographic characteristics and struggled with further challenges. For example, some variable-oriented studies identified students' degrees of burnout to also differ depending on their gender (Worly et al., 2019) and age (Aguayo et al., 2019). Since these results are inconsistent, however, no legitimate inferences can be derived. Other results indicated, for example, that elevated burnout symptoms associate with further adverse experiences such as more academic procrastination (Balkis, 2013), increased university dropout intentions (Mostert & Pienaar, 2020), and reduced study- and life satisfaction (Atalayin et al., 2015; Cazan et al., 2015). As aforementioned, prior empirical studies identified those experiences as strong predictors of academic success (Antaramian, 2017; Faas et al., 2018; Goroshit, 2018; Peixoto et al., 2021; Scheunemann, 2021). Person-oriented methods can cast light on whether these experiences possibly cooccur and differ at the intra-individual level.

3. The current study

Graduating with a diploma from higher education has numerous benefits for students (Baum et al., 2013). Globally, however, several students struggle to manage the challenges on the road to this success (Stallman & Hurst, 2016) and experience detrimental burnout symptoms (Salmela-Aro et al., 2022). Theoretical models assume that these symptoms develop sequentially (Leiter & Maslach, 1988) and vary in their degree depending on the demands and resources of individuals (Demerouti et al., 2001). Considering this, it seems conceivable that students' patterns (i.e., latent profiles) of burnout symptoms can differ. The examination of students' profiles is indispensable to understand how these symptoms interplay at the intra-individual level and what students' specific experiences, challenges, and needs are. So far, empirical evidence on such profiles is limited to Italian and Finnish university students. Caution should be exercised in generalizing this evidence to other student groups as students experience different challenges, possess varying resources, and therefore have different vulnerabilities to burnout symptoms.

Overall, the current study had three overarching goals. First, we conducted two online-studies and investigated whether *university students in Germany* showed similar profiles of burnout symptoms as previously identified in the Finnish and Italian higher education contexts (Portoghese et al., 2018; Salmela-Aro & Read, 2017; *Research Question 1*). In both studies, we recruited the students at the beginning of the 2020 summer semester. This was the first online-semester because of the outbreak of COVID-19. All students who were enrolled at accredited German universities could participate (exception: in Study 1, participation was only possible for students who were studying a STEM discipline, economics, law, or humanities). To address our research questions, we used cross-sectional data (i.e., recommended for exploring the potential structure of latent profiles; Leiter & Maslach, 2016) and conducted latent profile analysis (Ferguson et al., 2020). Since theoretical models assume that burnout symptoms develop sequentially (e.g., Golembiewski, 1986; Leiter & Maslach, 1988) and the symptoms describe distinct experiences, there could be many distinct profiles in our studies. We therefore compared several profile solutions. Considering prior research, however, we expected to identify at least two profiles: (1) a profile with high scores on all symptoms and (2) a profile with low scores on all symptoms (Portoghese et al., 2018; Salmela-Aro &

Read, 2017).

To validate and receive a more holistic view of the identified profiles, we next sought to shed initial light on the relation of the profiles with sociodemographic characteristics and concurrent study behavior and experiences. We first examined whether students' gender, age, and study progress predicted their probability of belonging to a specific profile (*Research Question 2*). Given lacking findings from person-oriented studies, we had no specific expectations about the predictive role of gender and age in profile membership. Considering prior findings from Salmela-Aro and Read (2017), however, we expected students in profiles with more pronounced burnout symptoms to be in later stages of their studies. Subsequently, we assessed if the profiles differed regarding other adverse experiences, namely academic procrastination, university dropout intentions, study satisfaction (satisfaction with taught contents, study conditions, coping with study-related stress), and life satisfaction (*Research Question 3*). Empirical studies identified these particular experiences as strong predictors of academic success (Antaramian, 2017; Faas et al., 2018; Goroshit, 2018; Peixoto et al., 2021; Scheunemann, 2021). Considering prior variable-oriented results (Atalayin et al., 2015; Balkis, 2013; Cazan et al., 2015; Rudman & Gustavsson, 2012), we expected students in profiles with higher burnout symptoms to report more unfavorable scores on these phenomena.

Summarizing, the theoretical contribution of this study particularly lies in complementing the existing knowledge on (1) the multidimensionality of burnout symptoms by examining their interplay at the intra-individual level, (2) intra-individual patterns of burnout symptoms, and (3) the association of such patterns with concurrent study behavior and experiences. This knowledge can shed valuable light on students' specific needs and illuminate ideas for designing tailored and targeted prevention- and intervention programs (cf. Leiter & Maslach, 2016).

4. Method

Given that the recruitment and characteristics of the two samples differed, we describe them separately in the following. Thereafter, we provide information about the utilized measures and statistical analyses, which were similar for both studies.

4.1. Sample 1 and procedure

Simultaneously at three accredited German universities, we conducted a longitudinal study with the superordinate goal to examine antecedents of students' university dropout intentions. Overall, the study included thirteen measurement points spread over six semesters (2018/2019 fall semester to 2021 summer semester). In the current research, we only used relevant data from the beginning (T_6) of the 2020 summer semester (i.e., to compare whether similar results can be found as in Study 2). In this semester, most students made first experiences with online learning and experienced several pandemic-related challenges as well as threats to their resources. These unprecedented experiences made students generally more susceptible to burnout symptoms (Salmela-Aro et al., 2022). The Ethical Committee of Bielefeld University gave ethical approval prior to data collection. We recruited at T_1 by contacting students during their lectures, providing concise information about the study, and distributing contact forms that interested students filled out. Shortly afterward, these students obtained more detailed study-related information and a gift worth € 5 at an introductory session and gave informed written consent for voluntary participation. Links forwarding students to the online surveys were then sent via e-mail. Offered incentives included moreover up to € 121 for participating at all thirteen measurement occasions at the end of the 2021 summer semester, where the exact monetary amount depended on students' individual compliance rate.

Similar to Salmela-Aro and Read (2017), we excluded two students from all analyses as no other students reported to be diverse and a representative "diverse" group did not emerge. A reliable comparison between female, male, and diverse students' odds of belonging to a particular profile would not have been possible. After this exclusion, the sample at T_6 included $N = 597$ ($n = 395$ female, $n = 202$ male) university students enrolled in STEM disciplines, economics, law, and humanities. On average, students were 22.74 ($SD = 2.88$) years old and had studied 6.19 ($SD = 3.28$) semesters at university.

4.2. Sample 2 and procedure

Our second longitudinal study had the overarching goal to examine the well-being, study motivation, study behavior, and academic outcomes of students enrolled in universities in Germany. Overall, this study comprised three measurement points spread over the 2020 summer semester. As in Study 1, we used relevant data from the beginning (T_1) of this first online semester. Thereby, we sought to gain additional insights into students' burnout symptoms during the pandemic and to compare the results between two independent studies. The data was collected about one week before T_6 of Study 1. The Ethical Committee of the Psychology Department of University of Münster gave ethical approval before data collection. We recruited at T_1 by contacting students from various German universities through social media platforms and universities' media officers who sent students brief study-related information via e-mail. Students who were interested in voluntary participation accessed the online survey by following a given link. Before answering the survey questions, students obtained more detailed study-related information and gave informed written consent. Offered incentives included vouchers worth 20 €, 25 €, 50 €, and 100 € that could be won in a raffle as well as course credits for psychology students enrolled at the [name of university masked for peer review].

Similar to Study 1, we excluded three students from all analyses since no other students reported to be diverse. The final sample at T_1 included $N = 857$ ($n = 687$ female, $n = 170$ male) university students enrolled in various programs such as social sciences, STEM disciplines, economics, medical fields, humanities, and music. On average, students were 23.71 ($SD = 4.11$) years old and had studied 6.40 ($SD = 4.37$) semesters at university. Compared to students in Study 1, these students were thus, on average, slightly older and in

later stages of their studies.

4.3. Measures

We only provide information about the measures relevant to this study. For student burnout, academic procrastination, university dropout intentions, and study- and life satisfaction, a higher value indicated a higher expression in the respective construct. The McDonald's ω coefficients for all measures met the criterion of at least 0.70 (McDonald, 1999).

4.3.1. Sociodemographic characteristics

We assessed particular sociodemographic characteristics of students that we considered as potentially relevant predictors of their profiles of burnout symptoms. These included students' gender (1 = female, 2 = male), age, and study progress (i.e., number of semesters studied at university).

4.3.2. Student burnout symptoms

To examine student burnout symptoms, we used the German short version of the Maslach Burnout Inventory-Student Survey (MBI-SS-KV; Wörfel et al., 2015). The MBI-SS-KV consists of three interrelated but distinct burnout symptoms that are each measured with three items: *emotional exhaustion* (e.g., "Studying or attending a class is really a strain for me"; $\omega_{study1} = 0.85$, $\omega_{study2} = 0.79$), *cynicism* (e.g., "I have become less enthusiastic about my studies"; $\omega_{study1} = 0.90$, $\omega_{study2} = 0.82$), and *reduced professional efficacy* (e.g., "I believe that I cannot make an effective contribution to the classes that I attend"; $\omega_{study1} = 0.77$, $\omega_{study2} = 0.71$). The response scale ranged from 1 (*never*) to 7 (*always*).

4.3.3. Academic procrastination

Grunschel et al. (2013) adapted the German version of the Tuckman Procrastination Scale (TPS-d; Stöber & Joormann, 2001; Tuckman, 1991) to assess procrastination in students. We used this adapted version, which includes 16 items (e.g., I needlessly delay the completion of work in my studies, even if they are important"; $\omega_{study1} = 0.94$, $\omega_{study2} = 0.94$). The response scale ranged from 1 (*this is not at all true*) to 5 (*this is perfectly true*).

4.3.4. University dropout intentions

In Study 1, we used five items of Dresel and Grassinger (2013) that assess students' intentions to drop out of university or change their academic major (e.g., "I often think about dropping out of my current course of studies or changing my major"; ω = 0.84). Generally, similarities in the developmental process of these two types of intentions exist but their separation seems nonetheless more appropriate since their determinants can differ (Bäulke et al., 2022). In Study 2, we only assessed intentions to drop out of university by adapting three items of Dresel and Grassinger (2013; ω = 0.83). These items included (1) "I often think about dropping out from university permanently"; (2) "The thought often crosses my mind that studying is not for me"; and (3) a reversed item "I am sure studying is the right thing for me". In both studies, the response scale ranged from 1 (*absolutely false*) to 6 (*absolutely true*).

4.3.5. Study satisfaction

We assessed three dimensions of study satisfaction (Schiefele & Jacob-Ebbinghaus, 2006): *satisfaction with taught contents* (4 items; e.g., "I am satisfied with my subject to the extent that I would choose it again"; $\omega_{study1} = 0.85$, $\omega_{study2} = 0.88$), *satisfaction with conditions of studying* (3 items; e.g., "At my university, there is not sufficient attention paid to students concerns"; $\omega_{study1} = 0.83$, $\omega_{study2} = 0.81$), and *satisfaction with coping with (study-related) stress* (3 items; e.g., "I often feel tired and exhausted due to my studies"; $\omega_{study1} = 0.85$, $\omega_{study2} = 0.81$). The response scale ranged from 1 (*strongly disagree*) to 6 (*strongly agree*).

4.3.6. Life satisfaction

To examine university students' satisfaction with life, we used a one-item scale that showed good test-retest reliability and convergent, discriminant, and concurrent validity (Beierlein et al., 2014). Students answered the question "How satisfied are you with your life in general" on a scale ranging from 1 (*not satisfied at all*) to 10 (*completely satisfied*).

4.4. Statistical analyses

To identify the latent profiles of burnout symptoms in both studies (*Research Question 1*), we adopted a person-oriented approach and performed latent profile analysis (LPA) with a robust maximum likelihood (MLR) estimator in Mplus (Version 8.4; Muthén & Muthén, 1998–2017). LPA is a probabilistic, model-based cluster analytic method that specifies a latent categorial variable with k latent profiles to capture heterogeneity among individuals. In other words, this method assigns the individuals in the sample to one of k latent profiles based on their scores on continuous variables (e.g., mean scores on burnout symptoms; cf. Lubke & Muthén, 2005). LPA aim to uncover hidden homogenous subgroups (i.e., groups that share similar patterns of responses on studied phenomena) within a heterogeneous population (Ferguson et al., 2020).

Given that the optimal number of profiles for a sample is a priori unknown in LPA, we estimated nested models with increasing number of profiles and compared their fit with commonly used statistical criteria outlined in Ferguson et al. (2020): Loglikelihood (LL), the Bayesian Information Criterion (BIC), sample size-adjusted BIC (SABIC), Akaike Information Criterion (AIC), Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMRT), Bootstrapped Likelihood Ratio Test (BLRT), and entropy values. Lower LL, BIC, SABIC, and

Table 1
Descriptive statistics and latent correlations for all study variables.

Scales	M_{study1} (SD)	M_{study2} (SD)	1	2	3	4	5	6	7	8	9	10	11	12
1. Gender[a]	—	—	—	.12**	.02	−0.01	.01	−0.03	.08*	−0.02	.06	.09*	−0.02	.02
2. Age	22.74 (2.88)	23.71 (4.11)	.08*	—	.48**	.01	.04	−0.05	.03	−0.01	−0.10**	−0.07*	−0.02	.02
3. Study Progress[b]	6.19 (3.28)	6.40 (4.37)	.07	.53**	—	.08*	.08*	−0.03	.05	−0.06	−0.15**	−0.12**	−0.01	.04
4. Emotional Exhaustion	3.49 (1.26)	3.01 (1.34)	−0.02	.04	−0.01	—	.52**	.63**	.37**	−0.51**	−0.38**	−0.70**	−0.42**	.44**
5. Cynicism	2.67 (1.32)	2.33 (1.32)	.06	.04	−0.01	.49**	—	.53**	.36**	−0.72**	−0.32**	−0.39**	−0.38**	.59**
6. Reduced Professional Efficacy	3.17 (1.25)	3.08 (1.30)	−0.06	.02	.02	.51**	.64**	—	.47**	−0.47**	−0.32**	−0.51**	−0.38**	.50**
7. Academic Procrastination	2.73 (0.81)	2.62 (0.83)	.08	.13**	.16**	.32**	.35**	.40**	—	−0.38**	−0.20**	−0.27**	−0.29**	.35**
8. Satisfaction with Study Contents	4.13 (0.98)	4.47 (1.00)	.03	−0.06	−0.05	−0.43**	−0.65**	−0.51**	−0.33**	—	.39**	.42**	.40**	−0.58**
9. Satisfaction with Study Conditions	3.71 (1.10)	3.65 (1.17)	−0.04	−0.08*	−0.08*	−0.39**	−0.28**	−0.28**	−0.18**	.21**	—	.41**	.21**	−0.28**
10. Satisfaction with Stress Coping	3.96 (1.13)	4.13 (1.09)	.04	−0.11**	−0.07	−0.72**	−0.41**	−0.49**	−0.28**	.41**	.51**	—	.40**	−0.33**
11. Life Satisfaction	6.97 (1.74)	7.17 (1.73)	−0.03	−0.07	−0.07	−0.32**	−0.26**	−0.33**	−0.33**	.30**	.22**	.34**	—	−0.32**
12. University Dropout Intentions	2.03 (1.03)	1.90 (1.05)	−0.04	.02	−0.08*	.34**	.60**	.48**	.28**	−0.58**	−0.15**	−0.37**	−0.28**	—

Note. Correlations below the diagonal are for Study 1 (N_{study1} = 597) and above the diagonal for Study 2 (N_{study2} = 857).

[a] 1 = females and 2 = males.

[b] number of semesters studied at university.

* $p < .05$.

** $p < .01$.

AIC indicate a better fit. Significant p-values for LMRT and BLRT indicate that the current model is superior than the previous, more parsimonious model with one profile less. Entropy values closer to 1 represent a more accurate classification of profiles. We additionally considered the interpretability, distinguishability, and sample size of the identified latent profiles. For example, (1) a model with more profiles is not beneficial for theory and practice when the profiles are not distinguishable (Ferguson et al., 2020); and (2) profiles consisting of less than 5% of the sample are typically regarded spurious and therefore rejected (Marsh et al., 2009).

To next examine how students' sociodemographic characteristics (gender, age, and study progress) predicted their profile membership (*Research Question 2*), we adopted the automatic 3-step approach (i.e., the R3STEP command in Mplus; Asparouhov & Muthén, 2014). This 3-step approach considers classification error, avoids shifts in the number and meaning of the profiles when covariates are added to the model, and proceeds as follows (Vermunt, 2010): (1) determining the optimal number of profiles without including covariates in the model (i.e., in this step, we used the profile solution identified in our analyses for Research Question 1); (2) specifying individuals' probability of membership in each profile based on their specific posterior class membership probabilities that are obtained in the previous step; and (3) estimating multinomial logistic regression models to evaluate the association of the profiles and covariates. In addition to the regression estimates, we provide odds ratios that inform about the odds of belonging to a specific profile compared to the reference profile.

Lastly, we assessed whether the retained latent profiles differed regarding academic procrastination, university dropout intentions, and study- and life satisfaction (*Research Question 3*). To this end, we used the automatic 3-step Bolck-Croon-Hagenaars (BCH) approach (Bakk & Vermunt, 2016). The 3-step BCH approach also considers measurement error and avoids changes in profiles when variables are added to the model. Given the consideration of measurement error, this approach produces more reliable results than analysis of variance (ANOVA). A major weakness of ANOVA is that measurement errors are being ignored, which can lead to biased results (Nylund-Gibson et al., 2019). Specifically, the BCH approach proceeds as follows (Bakk & Vermunt, 2016; Nylund-Gibson et al., 2019): (1) determining the optimal number of profiles without including variables in the model (i.e., in this step, we used the profile solution identified in our analyses for Research Question 1); (2) estimating of the classification errors and the inverse logits for those error rates for each individual; (3) using these logits as weights and comparing means of the variables for each profile using Wald chi-square tests. Overall, these tests inform (1) whether significant profile differences in the variables generally exist (i.e., through overall equality tests of means across profiles), and (2) where the exact differences are (i.e., through comparisons of dyads of profiles; Back & Vermunt, 2016).

5. Results

Study 1 and Study 2 results are reported together below. Overall, these results show several similarities concerning descriptive statistics, bivariate correlations, profile solutions and associations between these profiles with concurrent study behavior and experiences.

5.1. Descriptive statistics and bivariate correlations

Separately for Study 1 and Study 2, Table 1 reports the descriptive statistics and bivariate correlations of all variables of interest. In both studies, the estimated means for emotional exhaustion and reduced professional efficacy were more pronounced (i.e., in the middle area) compared to those for cynicism. Burnout symptoms showed significant positive intercorrelations in both studies (r_{study1} = 0.49 to 0.64; r_{study2} = 0.52 to 0.63). In both studies, all burnout symptoms also showed significant positive correlations with university dropout intentions (r_{study1} = 0.34 to 0.60; r_{study2} = 0.44 to 0.59), and significant negative correlations with satisfaction with taught contents (r_{study1} = −0.43 to −0.65; r_{study2} = −0.47 to −0.72), study conditions (r_{study1} = −0.28 to −0.39; r_{study2} = −0.32 to −0.38), coping with (study-related) stress (r_{study1} = −0.41 to −0.72; r_{study2} = −0.39 to −0.70), and life (r_{study1} = −0.26 to −0.33; r_{study2} = −0.38 to −0.42). In Study 2, emotional exhaustion and cynicism further positively correlated with study progress (r_{study1} = 0.08; r_{study2} = 0.08), indicating that students who were in later stages of their studies reported more elevated exhaustion and cynical

Table 2
Statistical fit indices for different profile solutions.

Number of Profiles	LL	BIC	SABIC	AIC	Entropy	LMRT	BLRT
Study 1							
1	−2979.72	5997.80	5978.75	5971.45	—	—	—
2 (n_1 = 36%, n_2 = 64%)	−2779.52	5622.96	5591.21	5579.04	0.76	$p < .001$	$p < .001$
3 (n_1 = 33%, n_2 = 47%, n_3 = 20%)	−2719.90	5529.29	5484.84	5467.80	0.70	$p = .17$	$p < .001$
4 (n_1 = 28%, n_2 = 27%, n_3 = 43%, n_4 =2%)	−2667.07	5449.20	5392.05	5370.14	0.77	$p < .01$	$p < .001$
5 (n_1 = 40%, n_2 = 24%, n_3 = 1%, n_4 = 9%, n_5 = 26%)	−2655.36	5451.34	5381.50	5354.72	0.75	$p < .05$	$p < .01$
Study 2							
1	−4359.87	8760.25	8741.20	8731.73	—	—	—
2 (n_1 = 74%, n_2 = 26%)	−4025.63	8118.79	8087.03	8071.25	0.83	$p < .001$	$p < .001$
3 (n_1 = 55%, n_2 = 31%, n_3 = 14%)	−3927.61	7949.76	7905.30	7883.21	0.76	$p < .001$	$p < .001$
4 (n_1 = 27%, n_2 = 14%, n_3 = 55%, n_4 = 4%)	−3867.23	7856.01	7798.85	7770.45	0.80	$p < .05$	$p < .001$
5 (n_1 = 8%, n_2 = 41%, n_3 = 35%, n_4 = 12%, n_5 = 4%,)	−3827.95	7804.48	7734.62	7699.91	0.78	$p = .14$	$p < .001$

Note. N_{study1} = 597; N_{study2} = 857; LL = Loglikelihood; BIC = Bayesian Information Criterion; SABIC = sample size-adjusted BIC; AIC = Akaike Information Criterion; LMRT = Lo-Mendell-Rubin Likelihood Ratio Test; BLRT = Bootstrapped Likelihood Ratio Test.

attitudes.

5.2. University students' profiles of burnout symptoms

To provide first insights into German-speaking university students' profiles of burnout symptoms during the COVID-19 pandemic (cf. *Research Question 1*), we conducted LPA. Table 2 displays for both studies separately the statistical fit indices for different profile solutions. In both studies, the decreases in LL, BIC, SABIC, and AIC values and significant BLRT values ($p < .001$) indicated that the iterative addition of new profiles resulted in improved model fit, with the 5-profile solutions fitting best. Yet, the 4- and 5-profile solutions included profile sizes smaller than 5%, wherefore these profile solutions were rejected (cf. Ferguson et al., 2020) and the 3-profile solutions were deemed best because of sufficient profile sizes, superior fit indices compared to the 1- and 2-profile solutions, and adequate classification accuracy as assessed by entropy.

Table 3 reports and Figs. 1 and 2 display the mean burnout scores for the 3-profile solution in both studies. Similar profiles emerged in these studies, but with slight differences in size. Profile 1 ($N_{study1} = 198$ [33%], $N_{study2} = 477$ [55%]) was termed *well-functioning* as it contained those students with low scores on all burnout symptoms. Profile 2 ($N_{study1} = 279$ [47%], $N_{study2} = 262$ [31%]) was termed *moderately exhausted-inefficacious* as it included those students with moderate emotional exhaustion, low cynicism, and moderate reduced professional efficacy. Profile 3 ($N_{study1} = 120$ [20%], $N_{study2} = 118$ [14%]) was termed *burned-out* as it comprised students with moderately high scores on all burnout symptoms. The profile sizes indicate that most students reported low to moderate burnout symptoms.

5.2.1. Sociodemographic characteristics of students as predictors of their profile membership

To subsequently validate and obtain a more holistic view of the selected profiles, we adopted the automatic 3-step approach (Vermunt, 2010) and examined if gender, age, and study progress predicted profile membership (cf. *Research Question 2*). Table 4 presents the results for Study 1 and Study 2 separately. In both studies, none of these sociodemographics of students significantly predicted their membership in a specific profile, with the exception of gender in Study 1. The results of the multinomial logistic regression in Study 1 revealed that women were less likely to be assigned to the well-functioning profile than to the moderately exhausted-inefficacious profile (OR = 0.54). Yet, these results warrant careful interpretation as women were overrepresented (comprised 66% of this sample) and the results were not replicated in Study 2.

5.2.2. Profile differences in concurrent study behavior and experiences

To complement the knowledge about the profiles further, we used the automatic 3-step BCH approach (Bakk & Vermunt, 2016) and lastly assessed if the profiles differed regarding academic procrastination, university dropout intentions, and study- and life satisfaction (cf. *Research Question 3*). Separately for Study 1 and Study 2, Table 5 provides detailed results of the comparisons of dyads of profiles, including means, standard errors, and χ^2-tests. The overall equality tests of means across profiles were in both studies significant for academic procrastination ($\chi^2_{study1} = 95.94$, $p < .001$; $\chi^2_{study2} = 155.13$, $p < .001$), university dropout intentions ($\chi^2_{study1} = 173.92$, $p < .001$; $\chi^2_{study2} = 296.52$, $p < .001$), and satisfaction with taught contents ($\chi^2_{study1} = 240.11$, $p < .001$; $\chi^2_{study2} = 454.39$, $p < .001$), study conditions ($\chi^2_{study1} = 87.98$, $p < .001$; $\chi^2_{study2} = 109.16$, $p < .001$), coping with (study-related) stress ($\chi^2_{study1} = 266.62$, $p < .001$; $\chi^2_{study2} = 310.75$, $p < .001$), and life ($\chi^2_{study1} = 77.16$, $p < .001$; $\chi^2_{study2} = 144.09$, $p < .001$).

Compared to students in the well-functioning and moderately exhausted-inefficacious profiles, students in the burned-out profiles reported in both studies more academic procrastination, stronger university dropout intentions, and lower satisfaction with taught contents, study conditions, as well as life. In Study 1, we also found that students in the burned-out profiles reported lower satisfaction with coping with (study-related) stress than students in the other two profiles. In Study 2, this study satisfaction dimension only significantly differed between students in the burned-out and well-functioning profiles. Yet, in both studies, we moreover identified students in the moderately exhausted-inefficacious profiles to report more unfavorable scores on all studied variables than students in the well-functioning profiles.

Table 3
Descriptive statistics for overall sample and three latent profiles.

| Profiles	n (%)	Emotional exhaustion		Cynicism		Reduced professional efficacy	
		M	*SE*	*M*	*SE*	*M*	*SE*
Study 1							
Overall Sample	597 (100%)	3.49	.05	2.67	.05	3.17	.05
Well-functioning	198 (33%)	2.53	.13	1.61	.08	1.93	.16
Moderately Exhausted-Inefficacious	279 (47%)	3.70	.15	2.59	.29	3.44	.19
Burned-Out	120 (20%)	4.54	.27	4.56	.32	4.54	.25
Study 2							
Overall Sample	857 (100%)	3.01	.05	2.33	.05	3.08	.04
Well-functioning	477 (55%)	2.22	.07	1.58	.05	2.29	.07
Moderately Exhausted-Inefficacious	262 (31%)	3.74	.14	2.52	.13	3.85	.13
Burned-Out	118 (14%)	4.44	.18	4.87	.16	4.47	.17
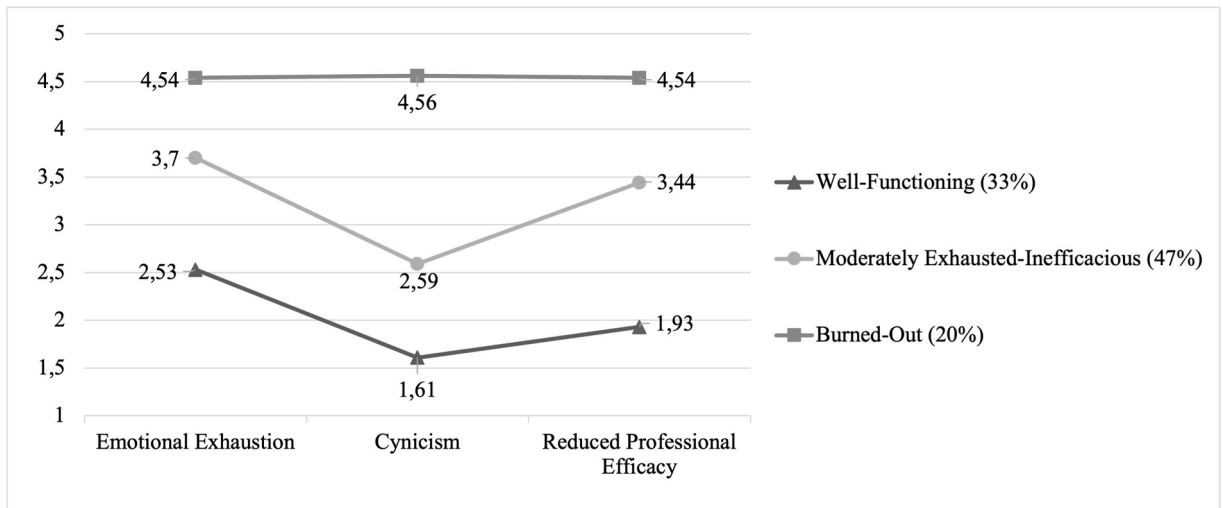
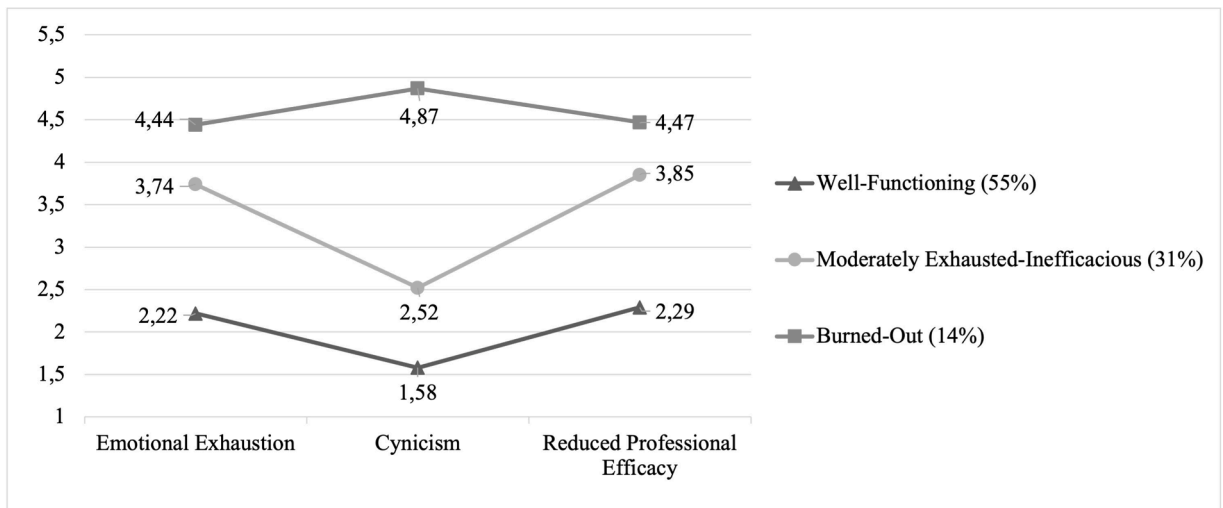**Fig. 1.** Study 1: Plot of Means for Each Latent Profile (*N* = 597).

Fig. 2. Study 2: Plot of Means for Each Latent Profile (*N* = 857).

Table 4
Sociodemographic predictors of latent profile membership.

| Sociodemographic characteristics | Profile comparisons | | | | | | | | | | | |
| | Well-functioning vs. moderately exhausted-inefficacious | | | | Well-functioning vs. burned-Out | | | | Moderately exhausted-inefficacious vs. burned-Out | | | |
	β	SE	*p*-value	OR	β	SE	*p*-value	OR	β	SE	*p*-value	OR
Study 1												
Gender[a]	−0.63	.27	< 0.05	.54	−0.19	.27	.49	.83	.44	.30	.15	.65
Age	−0.02	.06	.76	.98	.03	.06	.60	1.03	.05	.04	.25	.95
Study Progress[b]	.01	.05	.96	1.00	.02	.04	.68	1.02	.02	.05	.77	.99
Study 2												
Gender[a]	−0.26	.27	.32	1.31	−0.06	.28	.83	.94	.21	.35	.55	1.23
Age	−0.03	.03	.38	1.03	.01	.03	.57	1.01	.04	.03	.22	1.04
Study Progress[b]	.02	.03	.38	.98	.01	.03	.65	1.01	−0.01	.03	.73	.99

Note. N_{study1} = 597; N_{study2} = 857; β = coefficient estimate; OR = odds ratio.
[a] 1 = females and 2 = males.
[b] = number of semesters studied at university.

Table 5
Profile differences in concurrent study behavior and experiences.

Studied phenomena	Profile 1 Well-functioning	Profile 2 moderately exhausted-inefficacious	Profile 3 burned-Out	Profile comparisons		
				1 vs. 2	1 vs. 3	2 vs. 3
	M (SE)	*M (SE)*	*M (SE)*	χ^2	χ^2	χ^2
Study 1						
Academic Procrastination	2.31 (0.07)	2.78 (0.05)	3.30 (0.08)	24.31***	95.63***	24.86***
University Dropout Intentions	1.44 (0.06)	1.93 (0.06)	3.24 (0.13)	27.74***	163.98***	71.64***
Satisfaction with Study Contents	4.89 (0.07)	4.07 (0.06)	3.06 (0.10)	71.42***	229.53***	65.08***
Satisfaction with Study Conditions	4.35 (0.09)	3.51 (0.07)	3.10 (0.11)	43.42***	77.65***	7.82**
Satisfaction with Coping with Stress	4.96 (0.07)	3.65 (0.07)	3.04 (0.11)	134.98***	212.44***	17.77***
Life Satisfaction	7.84 (0.12)	6.81 (0.12)	5.91 (0.21)	30.27***	64.98***	11.62**
Study 2						
Academic Procrastination	2.28 (0.04)	2.94 (0.06)	3.21 (0.08)	69.61***	111.83***	6.21*
University Dropout Intentions	1.38 (0.04)	2.19 (0.08)	3.32 (0.12)	77.40***	230.18***	53.64***
Satisfaction with Study Contents	5.02 (0.04)	4.18 (0.06)	2.95 (0.10)	115.70***	387.77***	101.18***
Satisfaction with Study Conditions	4.06 (0.06)	3.25 (0.08)	2.91 (0.12)	52.84***	76.06***	4.78*
Satisfaction with Coping with Stress	4.76 (0.05)	3.37 (0.08)	3.37 (0.11)	211.46***	133.46***	0.01
Life Satisfaction	7.84 (0.07)	6.73 (0.13)	5.55 (0.21)	46.28***	107.73***	19.73***

Note. $N_{\text{study1}} = 597$; $N_{\text{study2}} = 857$.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

6. Discussion

Graduation from university bears various benefits for students (Baum et al., 2013). Yet, the road to this achievement can be challenging (Stallman & Hurst, 2016). Globally, several students struggle to manage challenges and experience burnout symptoms (Salmela-Aro et al., 2022). So far, empirical evidence on students' specific patterns (i.e., latent profiles) of burnout symptoms is scarce (Portoghese et al., 2018; Salmela-Aro & Read, 2017) but essential for understanding how these symptoms interplay at the intra-individual level and for designing individually tailored support. In addition, limited evidence exists on the association of these patterns with students' sociodemographic characteristics and concurrent study behavior and experiences. However, such insights are paramount for a more comprehensive understanding of students' individual challenges and needs. Overall, we aimed to complement the existing knowledge about student burnout symptoms and suggest practical implications for preventing and reducing student burnout symptoms. To this end, we conducted two online-studies with university students in Germany during the COVID-19 pandemic.

6.1. University students' profiles of burnout symptoms

Latent profile analyses indicated that university students in Germany display different profiles of burnout symptoms (cf. *Research Question 1*). Overall, the profile sizes indicated that most students reported low to moderate burnout symptoms during the COVID-19 pandemic. In general, this is a fortunate but somewhat unexpected finding since students were subjected to many novel demands (Browning et al., 2021). Seemingly, most students possessed sufficient resources to manage these demands and prevent burnout symptoms (cf. Demerouti et al., 2001).

Specifically, in Study 1 and Study 2, three groups of students emerged, each showing a specific symptom pattern. Consistent with some prior research in the university and school context (Salmela-Aro & Read, 2017; Salmela-Aro & Upadyaya, 2020, 2020; Tuominen-Soini & Salmela-Aro, 2014), the three profiles comprised the *well-functioning, burned-out,* and *moderately exhausted-inefficacious profiles.* The well-functioning profiles ($N_{\text{study1}} = 198$ [33%], $N_{\text{study2}} = 477$ [55%]) included students with low burnout symptoms. Contrary, the burned-out profiles ($N_{\text{study1}} = 120$ [20%], $N_{\text{study2}} = 118$ [14%]) included students with moderately high burnout symptoms. It is worrisome that some students already showed such elevated levels at the beginning of the semester since these symptoms are likely to worsen as the semester progresses because of increasing academic demands (e.g., workload, pressure of final exams) in particular. The COR Theory (Hobfoll, 1989) and the JD-R Model (Demerouti et al., 2001) stated that an imbalance between demands and resources trigger the emergence of burnout symptoms. Compared to students in the burned-out profiles, students in the well-functioning profiles thus possibly possessed more resources that helped managing demands and preventing burnout symptoms.

Lastly, the *moderately exhausted-inefficacious profile* ($N_{\text{study1}} = 279$ [47%], $N_{\text{study2}} = 262$ [31%]) contained students with moderate emotional exhaustion, low cynicism, and moderate reduced professional efficacy. University and high school students in Finland showed a similar profile (Salmela-Aro & Read, 2017; Salmela-Aro & Upadyaya, 2020; Tuominen-Soini & Salmela-Aro, 2014). A

particularly interesting characteristic of this profile is that *cynicism is the least pronounced burnout symptom*. Cynicism in students may thus manifest last in the burnout process, which would not align with tenets of the developmental burnout process model (Leiter & Maslach, 1988) and of the model by Golembiewski (1986). In students, the manifestation of cynicism could be the last straw, potentially leading to detrimental effects such as dropout from university (cf. Brockway et al., 2002). A second important characteristic of this profile is that *reduced professional efficacy is not the least pronounced burnout symptom*. So far, most researchers considered exhaustion and cynicism the core symptoms of burnout, wherefore reduced professional efficacy was often excluded from analyses. A central rational for this exclusion is that occupational studies in particular found this symptom to weakly correlate with the other two symptoms (cf. Mäkikangas & Kinnunen, 2016). In the educational context, however, this exclusion does not seem justified because reduced professional efficacy correlated strongly with exhaustion and cynicism in our studies and students' profiles of burnout symptoms revealed that reduced professional efficacy combines with the other two symptoms at the intra-individual level (cf. Salmela-Aro & Read, 2017; Salmela-Aro & Upadyaya, 2020). In addition, psychometric research indicated that reduced professional efficacy is an underlying symptom of student burnout (e.g., Portoghese et al., 2018; Turhan et al., 2021). Besides, reduced professional efficacy reflects a strong determinant of academic success (Schneider & Preckel, 2017) and thus, generally deserves particular consideration in educational research.

6.1.1. Sociodemographic characteristics of students as predictors of their profile membership

Some prior literature pointed to meaningful gender, age, and study progress differences in burnout symptoms in university students (Aguayo et al., 2019; Salmela-Aro & Read, 2017). We examined if these sociodemographic characteristics of students also predicted their membership in a specific profile (cf. *Research Question 2*). In Study 1, we found that female students had significantly higher odds of belonging to the moderately exhausted-inefficacious profile than the well-functioning profile. This finding aligns with prior results from Salmela-Aro and Read (2017), showing that female students experienced more exhaustion and inadequacy than male students. Greater emotional involvement of females in stressful life events and their greater susceptibility to the negative effects of those events (cf. Cohen et al., 2019; Kniffin et al., 2021) could account for this finding. In Study 2, however, gender did not significantly predict students' profile membership, indicating that our findings in this regard are inconsistent across the studies and, thus, warrant careful interpretation. In both studies, students' age and study progress did not predict their probability of belonging to a certain profile. Contrary, Salmela-Aro and Read (2017) found that students with overall higher burnout symptoms were in later stages of their studies. Given these discrepant results, more empirical research on these issues is necessary. On the one hand, it seems conceivable that students in lower semesters are at higher risk of burnout symptoms since they typically possess less experiences in managing study-related demands. On the other hand, students in later semesters could be at higher risk because of perhaps more adverse experiences (e.g., impaired academic performance, difficulty managing advanced taught contents, conflicts with peers, and financial difficulties) throughout their more advanced studies.

6.1.2. Profile differences in concurrent study behavior and experiences

The identified profiles of burnout symptoms significantly differed regarding concurrent study behavior and experiences (cf. *Research Question 3*). Congruent with prior variable-oriented studies and our expectations, the results indicated that students with the most pronounced burnout symptoms (i.e., burned-out profiles) also reported more unfavorable scores regarding academic procrastination (Balkis, 2013), university dropout intentions (Mostert & Pienaar, 2020), study satisfaction (satisfaction with taught contents, study conditions, coping with study-related stress), and life satisfaction (Atalayin et al., 2015; Cazan et al., 2015). Put succinctly, these findings make apparent that students in the burned-out profiles seemed to concurrently engage in dysfunctional study behavior and undergo other adverse experiences. A smaller proportion of students belonged to these profiles ($N_{study1} = 120$ [20%], $N_{study2} = 118$ [14%]). To achieve reductions in those students' pronounced symptom levels, the mitigation of their concurrent maladaptive experiences could possibly help. When their challenges and needs remain unaddressed, these students may decide to drop out of university. In particular, their elevated dropout intentions strengthen this assumption as theoretical models (Bean & Metzner, 1985) and empirical research (Bäulke et al., 2022) stated that these intentions reflect the strongest predictors of actual dropout. In higher education, student dropout is a cause for concern because of its high prevalence (up to 50%; Ulriksen et al., 2010; Organization for Economic Co-Operation and Development [OECD] 2018) and link with adverse effects for students, institutions, and society (Faas et al., 2018; Schnepf, 2017).

6.2. Practical implications

Given that the manifestation of burnout symptoms can differ among students, tailored prevention and intervention programs seem imperative (cf. Leiter & Maslach, 2016). Several students had low to moderate symptom levels at the beginning of the semester. Yet, these levels can increase as the semester progresses (cf. COR Theory, Hobfoll, 1989; see also Rudman & Gustavsson, 2012). Generally, the probability of developing such symptoms in a demanding university context appears to be high. Therefore, we recommend offering preventive support for all student groups that is tailored to each burnout symptom. When some symptoms are particularly pronounced, we suggest their treatment should be given priority. Treatments should also consider whether reducing dysfunctional study behavior and other adverse experiences that seemingly cooccur with burnout symptoms may also help alleviate those symptoms.

An accumulation of study demands and availability of limited resources to manage these demands can, in particular, trigger the development of *emotional exhaustion* (i.e., tiredness, energy loss). To address these feelings, interventions should therefore focus on alleviating psychological distress (e.g., Cognitive-Behavioral Stress Management; Regehr et al., 2013), enhancing relaxation (e.g., Mindfulness Meditation; Bamber & Schneider, 2016), and broadening the resource repertoires of students. The promotion of

psychological resilience as a psychological resource, for example, could help students to rapidly bounce back and subjectively recover from stressors (cf. Chmitorz et al., 2018; Steinhardt & Dolbier, 2008).

Unfulfilled expectations regarding the university environment and program can, in particular, lead to the emergence of *cynical and detached attitudes* towards one's studies (Brockway et al., 2002). To prevent these attitudes, university administrators should therefore convey accurate university-related information. Generally, such attitudes could also emerge when students dislike study-related tasks and perceive them as irrelevant. Thus, strengthening their perceived intrinsic value (i.e., enjoyment of study-related tasks) and utility value (i.e., personal importance or usefulness of study-related tasks) could also help to reduce such attitudes (for summaries of value interventions see Hulleman et al., 2016; Rosenzweig & Wigfield, 2016).

Lastly, feelings of *reduced professional efficacy* (i.e., sense of being incompetent as a student and uncapable to successfully master study-related tasks) can be addressed through various types of interventions. For example, an increase in the self-efficacy beliefs of students can be achieved through providing constructive feedback, enhancing mastery experiences and vicarious learning experiences, and having students reflect on their individual character strengths (see the review of Bartimote-Aufflick et al., 2016; Usher & Pajares, 2008).

6.3. Limitations and future research

Our study also harbors some limitations that warrant attention. First, we exclusively used self-report data that could be subject to social desirability and acquiescence response bias. To minimize this bias, the participation in our studies was anonymous and respondents received confidentiality assurance before data collection. Generally, given that students' subjective burnout symptoms, academic procrastination, university dropout intentions, and study- and life satisfaction are by nature self-perceptions and evaluations, the use of self-reports seems inevitable and a necessary method of assessment (cf. Spector, 2006). We nevertheless encourage future research to supplement our findings with the inclusion of objective measures (e.g., physiological signs of burnout, actual dropout, and academic success in form of grades).

Second, we cannot generalize the identified profiles and their association with other examined variables (i.e., sociodemographic characteristics, academic procrastination, university dropout intentions, and study- and life satisfaction) to the entire student population. In Study 1 and Study 2, we only included students enrolled at German universities, and women were overrepresented (Study 1: 66% of the sample; Study 2: 80% of the sample). In addition, both studies were conducted during the COVID-19 pandemic, wherefore the generalizability of the current results are limited to this time period. Besides, we cannot tease out specifically how the pandemic might have impacted our results. Given these limitations, we encourage future research to assess whether similar profiles can be identified during and after the pandemic, as well as across countries with more equally represented student groups.

Third, we encourage future research to complement the understanding of students' profiles of burnout symptoms by also considering the physical and cognitive aspects of exhaustion. The Oldenburg Burnout Inventory for Students (OLBI-S; Reis et al., 2015) captures these aspects but not the MBI-SS (Schaufeli et al., 2002), whose German short version we used (Wörfel et al., 2015). To deepen this understanding further, we encourage future research to also consider a more differentiated assessment of cynicism. So far, existing student burnout measures only assess cynical attitudes directed at one's studies in general. The Cynical Attitudes Toward College Scale (CATCS; Brockway et al., 2002), for example, also captures such attitudes targeted towards specific aspects of one's studies (e.g., towards courses, availability of social opportunities on campus, and decisions of administrators). Moreover, we encourage researchers (1) to examine the predictive role of additional sociodemographic characteristics (e.g., grade point average and academic major) in profile membership, and (2) to compare the profiles on a wider selection of concurrent behaviors (e.g., study engagement) and experiences (e.g., time pressure). Similar to Salmela-Aro and Read (2017), for example, researchers could apply the JD-R Model (Demerouti et al., 2001) for this purpose.

Another avenue for future research is to investigate the stability of students' profiles of burnout symptoms (e.g., through latent transition analyses; Muthén & Muthén, 2000). Since these symptoms develop as time progresses (Hobfoll, 1989), students could theoretically transition to another profile over time. Using cross-sectional data, this study provided initial evidence on profiles of burnout symptoms *in students in Germany amid the COVID-19 pandemic* and on the association of these profiles with concurrent study behavior and experiences.

7. Conclusion

Given their adverse effects, burnout symptoms in university students have garnered a great deal of research attention in the past two decades (Madigan & Curran, 2020). The current research adopted a person-oriented approach and offered some interesting new evidence on these symptoms in German higher education. First, students were classifiable into homogenous subgroups that shared similar symptom patterns. That is, distinct profiles of burnout symptoms existed in university students in Germany during the COVID-19 pandemic. Most students belonged to profiles with low to moderate burnout symptoms, but some students seemingly required urgent support considering their worrisome symptom levels. The presence of distinct profiles prompt calls for tailored and targeted burnout interventions (Mäkikangas & Kinnunen, 2016), as "one size does not fit all" (Leiter & Maslach, 2016, p. 99). Second, the discovered profiles indicated that students in profiles with higher burnout symptoms also engaged in dysfunctional study behavior and experienced other adverse experiences. This evidence has important implications for practice in particular, in terms of considering these concurrent challenges for the design of effective interventions. Third, the profiles challenged the idea that reduced professional efficacy is no core symptom of student burnout, as this symptom was prevalent in many students and possibly develops and manifests before cynicism. Perhaps, the additional manifestation of cynicism in students is the last straw that breaks the camel's back.

Author note

Declaration of Competing Interest

All authors declare that they have no conflict of interest.

References

Aguayo, R., Cañadas, G. R., Assbaa-Kaddouri, L., Ramírez-Baena, L., & Ortega-Campos, E. (2019). A risk profile of sociodemographic factors in the onset of academic burnout syndrome in a sample of university students. *International Journal of Environmental Research and Public Health, 16*(5), 707. https://doi.org/10.3390/ijerph16050707

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). https://doi.org/10.1176/appi.books.9780890425596

Antaramian, S. (2017). The importance of very high life satisfaction for students' academic success. *Cogent Education, 4*(1), Article 1307622. https://doi.org/10.1080/2331186X.2017.1307622

Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling: A Multidisciplinary Journal, 21*(3), 329–341. https://doi.org/10.1080/10705511.2014.915181

Atalayin, C., Balkis, M., Tezel, H., Onal, B., & Kayrak, G. (2015). The prevalence and consequences of burnout on a group of preclinical dental students. *European Journal of Dentistry, 9*(03), 356–363. https://doi.org/10.4103/1305-7456.163227

Auerbach, R. P., Mortier, P., Bruffaerts, R., Alonso, J., Benjet, C., Cuijpers, P., et al. (2018). WHO WMH-ICS Collaborators.WHO World Mental Health Surveys International College Student Project: Prevalence and distribution of mental disorders. *Journal of Abnormal Psychology, 127*(7), 623–638. https://doi.org/10.1037/abn0000362

Bakk, Z., & Vermunt, J. K. (2016). Robustness of stepwise latent class modeling with continuous distal outcomes. *Structural Equation Modeling: A Multidisciplinary Journal, 23*(1), 20–31. https://doi.org/10.1080/10705511.2014.955104

Balkis, M. (2013). The relationship between academic procrastination and students' burnout. *Hacettepe Üniversitesi Eğitim Fakültesi Dergisi [Hacettepe University Journal of Education], 28*(1), 53–63.

Bamber, M. D., & Schneider, J. K. (2016). Mindfulness-based meditation to decrease stress and anxiety in college students: A narrative synthesis of the research. *Educational Research Review, 18*, 1–32. https://doi.org/10.1016/j.edurev.2015.12.004

Bartimote-Aufflick, K., Bridgeman, A., Walker, R., Sharma, M., & Smith, L. (2016). The study, evaluation, and improvement of university student self-efficacy. *Studies in Higher Education, 41*(11), 1918–1942. https://doi.org/10.1080/03075079.2014.999319

Bäulke, L., Grunschel, C., & Dresel, M. (2022). Student dropout at university: A phase-orientated view on quitting studies and changing majors. *European Journal of Psychology of Education, 37*(3), 853–876. https://doi.org/10.1007/s10212-021-00557-x

Baum, S., Ma, J., & Payea, K. (2013). *Education pays, 2013: The benefits of higher education for individuals and society. Trends in higher education series*. New York: College.

Bean, J. P., & Metzner, B. S. (1985). A conceptual model of nontraditional undergraduate student attrition. *Review of Educational Research, 55*(4), 485–540. https://doi.org/10.3102/00346543055004485

Beierlein, C., Kovaleva, A., László, Z., Kemper, C. J., & Rammstedt, B. (2014). *Eine single-item-skala zur erfassung der allgemeinen lebenszufriedenheit: Die kurzskala lebenszufriedenheit-1 (L-1) [A single-item scale measuring general life satisfaction]*. Köln, Germany: GESIS (GESIS Working Papers 2014, 33) https://www.gesis.org/fileadmin/kurzskalen/working_papers/L1_WorkingPapers_2014-33.pdf.

Brockway, J. H., Carlson, K. A., Jones, S. K., & Bryant, F. B. (2002). Development and validation of a scale for measuring cynical attitudes toward college. *Journal of Educational Psychology, 94*(1), 210–224. https://doi.org/10.1037/0022-0663.94.1.210

Browning, M., Larson, L. R., Sharaievska, I., Rigolon, A., McAnirlin, O., Mullenbach, L., et al. (2021). Psychological impacts from COVID-19 among university students: Risk factors across seven states in the United States. *PloS one, 16*(1), Article e0245327. https://doi.org/10.1371/journal.pone.0245327

Cazan, A. M., & Năstasă, L. E. (2015). Emotional intelligence, satisfaction with life and burnout among university students. *Procedia-Social and Behavioral Sciences, 180*, 1574–1578. https://doi.org/10.1016/j.sbspro.2015.02.309

Chmitorz, A., Kunzler, A., Helmreich, I., Tüscher, O., Kalisch, R., Kubiak, T., et al. (2018). Intervention studies to foster resilience – a systematic review and proposal for a resilience framework in future intervention studies. *Clinical Psychology Review, 59*, 78–100. https://doi.org/10.1016/j.cpr.2017.11.002

Cohen, S., Murphy, M., & Prather, A. A. (2019). Ten surprising facts about stressful life events and disease risk. *Annual Review of Psychology, 70*, 577–597. https://doi.org/10.1146/annurev-psych-010418-102857

De Beer, L. T., Schaufeli, W. B., De Witte, H., Hakanen, J. J., Shimazu, A., Glaser, J., et al. (2020). Measurement invariance of the burnout assessment tool (BAT) across seven cross-national representative samples. *International Journal of Environmental Research and Public Health*, (15), 17. https://doi.org/10.3390/ijerph17155604

Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology, 86*(3), 499–512. https://doi.org/10.1037//0021-9010.86.3.499

Dresel, M., & Grassinger, R. (2013). Changes in achievement motivation among university freshmen. *Journal of Education and Training Studies, 1*(2), 159–173. https://doi.org/10.11114/jets.v1i2.147

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

Faas, C., Benson, M. J., Kaestle, C. E., & Savla, J. (2018). Socioeconomic success and mental health profiles of young adults who drop out of college. *Journal of Youth Studies, 21*(5), 669–686. https://doi.org/10.1080/13676261.2017.1406598

Ferguson, S. L., G., Moore, E. W., & Hull, D. M. (2020). Finding latent groups in observed data: A primer on latent profile analysis in Mplus for applied researchers. *International Journal of Behavioral Development, 44*(5), 458–468. https://doi.org/10.1177/0165025419881721

Galán-Santos, J. V., Polo, J., Rios-Carrasco, B., & Bullón, P. (2014). Burnout, depression and suicidal ideation in dental students. *Medicina Oral Patologia Oral y Cirugia Bucal, 19*(3), e206. https://doi.org/10.4317/medoral.19281

Golembiewski, R. T. (1986). The epidemiology of progressive burnout: A primer. *Journal of Health and Human Resources Administration*, 16–37. http://www.jstor.org/stable/25780258.

Goroshit, M. (2018). Academic procrastination and academic performance: An initial basis for intervention. *Journal of Prevention & Intervention in the Community, 46*(2), 131–142. https://doi.org/10.1080/10852352.2016.1198157

Grunschel, C., Patrzek, J., & Fries, S. (2013). Exploring different types of academic delayers: A latent profile analysis. *Learning and Individual Differences, 23*, 225–233. https://doi.org/10.1016/j.lindif.2012.09.014

Grützmacher, J., Gusy, B., Lesener, T., Sudheimer, S., & Willige, J. (2018). Gesundheit studierender in Deutschland 2017. *Ein kooperationsprojekt zwischen dem deutschen zentrum für Hochschul- und Wissenschaftsforschung.* der Freien Universität Berlin und der Techniker Krankenkasse. https://www.fachportal-paedagogik.de/literatur/vollanzeige.html?FId=1149030#vollanzeige.

Gusy, B., Wörfel, F., & Lohmann, K. (2016). Erschöpfung und Engagement im Studium: Eine Anwendung des Job Demands-Resources Modells [Exhaustion and engagement in university students: An application of the job demands–resources model]. *Zeitschrift für Gesundheitspsychologie, 24*(1), 41–53. https://doi.org/10.1026/0943-8149/a000153

Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist, 44*(3), 513–524. https://doi.org/10.1037/0003-066X.44.3.513

Hulleman, C. S., Barron, K. E., Kosovich, J. J., & Lazowski, R. A. (2016). Student motivation: Current theories, constructs, and interventions within an expectancy-value framework. In A. A. Lipnevich, F. Preckel, & R. D. Roberts (Eds.), *Psychosocial skills and school systems in the 21st century: Theory, research, and practice* (pp. 241–278). Springer International Publishing AG. https://doi.org/10.1007/978-3-319-28606-8_10

Jackson, E. R., Shanafelt, T. D., Hasan, O., Satele, D. V., & Dyrbye, L. N. (2016). Burnout and alcohol abuse/dependence among US medical students. *Academic Medicine, 91*(9), 1251–1256. https://doi.org/10.1097/ACM.0000000000001138

Kaggwa, M. M., Kajjimu, J., Sserunkuma, J., Najjuka, S. M., Atim, L. M., Olum, R., et al. (2021). Prevalence of burnout among university students in low-and middle-income countries: A systematic review and meta-analysis. *PLoS One, 16*(8), Article e0256402. https://doi.org/10.1371/journal.pone.0256402

Kniffin, K. M., Narayanan, J., Anseel, F., Antonakis, J., Ashford, S. P., Bakker, A. B., et al. (2021). COVID-19 and the workplace: Implications, issues, and insights for future research and action. *American Psychologist, 76*(1), 63–77. https://doi.org/10.1037/amp0000716

Kristanto, T., Chen, W. S., & Thoo, Y. Y. (2016). Academic burnout and eating disorder among students in Monash University Malaysia. *Eating Behaviors, 22*, 96–100. https://doi.org/10.1016/j.eatbeh.2016.03.029

Laursen, B., & Hoff, E. (2006). Person-centered and variable-centered approaches to longitudinal data. *Merrill-Palmer Quarterly, 52*(3), 377–389. https://doi.org/10.1353/mpq.2006.0029

Leiter, M. P., & Maslach, C. (1988). The impact of interpersonal environment on burnout and organizational commitment. *Journal of Organizational Behavior, 9*(4), 297–308. https://doi.org/10.1002/job.4030090402

Leiter, M. P., & Maslach, C. (2016). Latent burnout profiles: A new approach to understanding the burnout experience. *Burnout Research, 3*(4), 89–100. https://doi.org/10.1016/j.burn.2016.09.001

Lesener, T., Pleiss, L. S., Gusy, B., & Wolter, C. (2020). The study demands-resources framework: An empirical introduction. *International Journal of Environmental Research and Public Health, 17*(14), 5183. https://doi.org/10.3390/ijerph17145183

Lubke, G. H., & Muthén, B. (2005). Investigating population heterogeneity with factor mixture models. *Psychological Methods, 10*(1), 21–39. https://doi.org/10.1037/1082-989X.10.1.21

Madigan, D. J., & Curran, T. (2020). Does burnout affect academic achievement? A meta-analysis of over 100,000 students. *Educational Psychology Review*, 1–19. https://doi.org/10.1007/s10648-020-09533-1

Mäkikangas, A., & Kinnunen, U. (2016). The person-oriented approach to burnout: A systematic review. *Burnout Research, 3*(1), 11–23. https://doi.org/10.1016/j.burn.2015.12.002

Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling, 16*(2), 191–225. https://doi.org/10.1080/10705510902751010

McDonald, R. P. (1999). *Test theory: A unified treatment*. Lawrence Erlbaum Associates.

Mostert, K., & Pienaar, J. (2020). The moderating effect of social support on the relationship between burnout, intention to drop out, and satisfaction with studies of first-year university students. *Journal of Psychology in Africa, 30*(3), 197–202. https://doi.org/10.1080/14330237.2020.1767928

Muthén, B., & Muthén, L. K. (2000). Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research, 24*(6), 882–891. https://doi.org/10.1111/j.1530-0277.2000.tb02070.x

Muthén, L. K., & Muthén, B. O. (1998–2017). *Mplus user's guide*. Muthén & Muthén.

Nylund-Gibson, K., Grimm, R. P., & Masyn, K. E. (2019). Prediction from latent classes: A demonstration of different approaches to include distal outcomes in mixture models. *Structural Equation Modeling, 26*(6), 967–985. https://doi.org/10.1080/10705511.2019.1590146

Ochnik, D., Rogowska, A. M., Kuśnierz, C., Jakubiak, M., Schütz, A., Held, M. J., et al. (2021). Mental health prevalence and predictors among university students in nine countries during the COVID-19 pandemic: A cross-national study. *Scientific Reports, 11*(1), 18644. https://doi.org/10.1038/s41598-021-97697-3

OECD. (2018). *Education at a glance 2018*. Paris: OECD Publishing. https://doi.org/10.1787/eag-2018-en

Peixoto, E. M., Pallini, A. C., Vallerand, R. J., Rahimi, S., & Silva, M. V. (2021). The role of passion for studies on academic procrastination and mental health during the COVID-19 pandemic. *Social Psychology of Education, 24*(3), 877–893. https://doi.org/10.1007/s11218-021-09636-9

Portoghese, I., Leiter, M. P., Maslach, C., Galletta, M., Porru, F., D'Aloja, E., et al. (2018). Measuring burnout among university students: Factorial validity, invariance, and latent profiles of the Italian version of the Maslach Burnout Inventory Student Survey (MBI-SS). *Frontiers in Psychology, 9*, 2105. https://doi.org/10.3389/fpsyg.2018.02105

Regehr, C., Glancy, D., & Pitts, A. (2013). Interventions to reduce stress in university students: A review and meta-analysis. *Journal of Affective Disorders, 148*(1), 1–11. https://doi.org/10.1016/j.jad.2012.11.026

Reis, D., Xanthopoulou, D., & Tsaousis, I. (2015). Measuring job and academic burnout with the Oldenburg Burnout Inventory (OLBI): Factorial invariance across samples and countries. *Burnout Research, 2*(1), 8–18. https://doi.org/10.1016/j.burn.2014.11.001

Rosenzweig, E. Q., & Wigfield, A. (2016). STEM motivation interventions for adolescents: A promising start, but further to go. *Educational Psychologist, 51*(2), 146–163. https://doi.org/10.1080/00461520.2016.1154792

Rotenstein, L. S., Ramos, M. A., Torre, M., Segal, J. B., Peluso, M. J., Guille, C., et al. (2016). Prevalence of depression, depressive symptoms, and suicidal ideation among medical students: A systematic review and meta-analysis. *JAMA, 316*(21), 2214–2236. https://doi.org/10.1001/jama.2016.17324

Rudman, A., & Gustavsson, J. P. (2012). Burnout during nursing education predicts lower occupational preparedness and future clinical performance: A longitudinal study. *International Journal of Nursing Studies, 49*(8), 988–1001. https://doi.org/10.1016/j.ijnurstu.2012.03.010

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., & Upadyaya, K. (2020). School engagement and school burnout profiles during high school–The role of socio-emotional skills. *European Journal of Developmental Psychology, 17*(6), 943–964. https://doi.org/10.1080/17405629.2020.1785860

Salmela-Aro, K., Upadyaya, K., Ronkainen, I., & Hietajärvi, L. (2022). Study burnout and engagement during COVID-19 among university students: The role of demands, resources, and psychological needs. *Journal of Happiness Studies*, 1–18. https://doi.org/10.1007/s10902-022-00518-1

Schaufeli, W. B., Martínez, I. M., Pinto, A. M., Salanova, M., & Bakker, A. B. (2002). Burnout and engagement in university students: A cross-national study. *Journal of Cross-Cultural Psychology, 33*(5), 464–481. https://doi.org/10.1177/0022022102033005003

Scheunemann, A., Schnettler, T., Bobe, J., Fries, S., & Grunschel, C. (2021). A longitudinal analysis of the reciprocal relationship between academic procrastination, study satisfaction, and dropout intentions in higher education. *European Journal of Psychology of Education*, 1–24. https://doi.org/10.1007/s10212-021-00571-z

Schiefele, U., & Jacob-Ebbinghaus, L. (2006). Lernermerkmale und Lehrqualität als Bedingungen der Studienzufriedenheit. *Zeitschrift für Pädagogische Psychologie, 20*(3), 199–212. https://doi.org/10.1024/1010-0652.20.3.199

Schnepf, S. V. (2017). How do tertiary dropouts fare in the labour market? A comparison between EU countries. *Higher Education Quarterly, 71*(1), 75–96. https://doi.org/10.1111/hequ.12112

Spector, P. E. (2006). Method Variance in Organizational Research: Truth or Urban Legend? *Organizational Research Methods, 9*(2), 221–232. https://doi.org/10.1177/1094428105284955

Stallman, H. M., & Hurst, C. P. (2016). The university stress scale: Measuring domains and extent of stress in university students. *Australian Psychologist, 51*(2), 128–134. https://doi.org/10.1111/ap.12127

Steinhardt, M., & Dolbier, C. (2008). Evaluation of a resilience intervention to enhance coping strategies and protective factors and decrease symptomatology. *Journal of American College Health, 56*(4), 445–453. https://doi.org/10.3200/JACH.56.44.445-454

Stöber, J., & Joormann, J. (2001). Worry, procrastination, and perfectionism: Differentiating amount of worry, pathological worry, anxiety, and depression. *Cognitive Therapy and Research, 25*(1), 49–60. https://doi.org/10.1023/A:1026474715384

Sveinsdóttir, H., Flygenring, B. G., Svavarsdóttir, M. H., Thorsteinsson, H. S., Kristófersson, G. K., Bernharðsdóttir, J., et al. (2021). Predictors of university nursing student's burnout at the time of the COVID-19 pandemic: A cross-sectional study. *Nurse Education Today, 106*, Article 105070. https://doi.org/10.1016/j.nedt.2021.105070

Tuckman, B. W. (1991). The development and concurrent validity of the Procrastination Scale. *Educational and Psychological Measurement, 51*(2), 473–480. https://doi.org/10.1177/0013164491512022

Turhan, D., Scheunemann, A., Schnettler, T., Bäulke, L., Thies, D. O., Dresel, M., et al. (2021). Psychometric properties of the German short version of the Maslach Burnout Inventory – Student Survey. *European Journal of Health Psychology, 28*(2), 45–58. https://doi.org/10.1027/2512-8442/a000067

Ulriksen, L., Madsen, L. M., & Holmegaard, H. T. (2010). What do we know about explanations for drop out/opt out among young people from STM higher education programmes? *Studies in Science Education, 46*(2), 209–244. https://doi.org/10.1080/03057267.2010.504549

Usher, E. L., & Pajares, F. (2008). Sources of self-efficacy in school: Critical review of the literature and future directions. *Review of Educational Research, 78*(4), 751–796. https://doi.org/10.3102/0034654308321456

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis, 18*, 450–469. https://doi.org/10.1093/pan/mpq025

Wörfel, F., Gusy, B., Lohman, K., & Kleiber, D. (2015). Validation of the German short version of the Maslach-Burnout-Inventory for students (MBI-SS KV). *Zeitschrift für Gesundheitspsychologie, 23*(4), 193–198. https://doi.org/10.1026/0943-8149/a000146