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Profiles of risk factors for depressive and anxiety symptoms during the COVID-19 pandemic: A latent class analysis

Laura Kenntemich [a,b,*], Leonie von Hülsen [a], Ingo Schäfer [a], Maria Böttche [c,d], Annett Lotzin [a,b]

[a] Department of Psychiatry and Psychotherapy, University Medical Center Hamburg Eppendorf, Hamburg, Germany
[b] Department of Psychology, MSH Medical School Hamburg, Hamburg, Germany
[c] Division of Clinical Psychological Intervention, Freie Universität Berlin, Germany
[d] Forschungsabteilung, Zentrum ÜBERLEBEN, Berlin, Germany

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ABSTRACT

The COVID-19 pandemic has caused a high burden in the general population. The exposure to an accumulation of risk factors, as opposed to a single risk, may have been associated with higher levels of depressive and anxiety symptoms during the pandemic. This study aimed to (1) identify subgroups of individuals with distinct constellations of risk factors during the COVID-19 pandemic and (2) investigate differences in levels of depressive and anxiety symptoms. German participants ($N = 2245$) were recruited between June-September 2020 through an online survey (ADJUST study). Latent class analysis (LCA) and multiple group analyses (Wald-tests) were conducted to identify profiles of risk factors and examine differences in symptoms of depression (PHQ-9) and anxiety (GAD-2). The LCA included 14 robust risk factors of different domains, for example, sociodemographic (e.g., age), health-related (e.g., trauma), and pandemic-related (e.g., reduced income) factors. The LCA identified three risk profiles: High sociodemographic risk (11.7%), high social and moderate health-related risk (18.0%), and low general risk (70.3%). Individuals with high sociodemographic risk reported significantly higher symptom levels of depression and anxiety than the remaining groups. A better understanding of risk factor profiles could help to develop targeted prevention and intervention programs during pandemics.

1. Introduction

The COVID-19 pandemic has drastically affected everyone's lives and daily routines. Since the outbreak of the pandemic in March 2020, the global population has experienced multiple stressors and burdens. A growing number of studies suggest that these COVID-19-related stressors might have led to increased mental health impairments (Aknin et al., 2022). During the early phase of the pandemic, elevated symptoms of depression and anxiety have been reported worldwide (Castaldelli-Maia et al., 2021; de Sousa et al., 2021; Necho et al., 2021). Santomauro et al. (2021) reported an estimated global increase of 27.6% in major depression and 25.6% in anxiety disorders in the general population in 2020 due to the COVID-19 pandemic. An international meta-review (de Sousa et al., 2021) reported high prevalences of depression (26.9%) and anxiety (27.8%). However, all studies predominantly used Asian samples. A large-scale longitudinal UK study found the highest levels of depressive and anxiety symptoms at the onset of the lockdown in March 2020 (Fancourt et al., 2020). After the lockdown, the levels decreased and reached a plateau, possibly due to individual adaption of the circumstances. A large-scale, cross-sectional German study (Bäuerle et al., 2020) found an increased prevalence of 14.3% (vs. 5.6%) for depression and 16.8% (vs. 6.0%) for moderate generalized anxiety disorder (GAD) symptoms during the first wave of COVID-19 compared with representative German pre-COVID samples.

Depression and anxiety disorders are among the most common mental disorders worldwide (WHO, 2017) and often co-occur (Saha et al., 2021). Major depressive disorder (MDD) includes depressed mood, loss of interest, or pleasure, and secondary symptoms, such as weight loss, insomnia, hypersomnia, worthlessness, and guilt (DSM-V; APA 2013). Core symptoms of GAD are excessive anxiety and worry about several events or activities, occurring on most days and persisting for at least six months (DSM-V; APA 2013). GAD is also associated with at least three other physical or cognitive symptoms, for instance, restlessness, or impaired concentration. Having a depressive disorder or

* Corresponding author at: Department of Psychiatry and Psychotherapy, University Medical Center Hamburg Eppendorf, Martinistraße 52, Hamburg 20251, Germany.

E-mail address: l.kenntemich.ext@uke.de (L. Kenntemich).

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GAD has drastic effects on many areas of life and is associated with several adverse outcomes. These include decreased work productivity (Plaisier et al., 2010) and quality of life (Hohls et al., 2021), as well as impaired social functioning (Saris et al., 2017). Additionally, the economic costs of (treating) depression and anxiety disorders are high (Hoffman and Mychaskiw, 2008; Krauth et al., 2014). Taken together, first studies indicated an increase in depressive and anxiety symptoms at the onset of the COVID-19 pandemic. Given the individual and societal consequences, it is crucial to investigate which individuals were at high risk of developing depressive or anxiety symptoms.

From a theoretical perspective, the pandemic has brought along stressors that placed individuals at a higher risk of developing depressive or anxiety symptoms. Basic human psychological needs, such as attachment, control, pleasure, unpleasure avoidance, and self-enhancement (*consistency theory*; Grawe 2000), have been massively threatened by previously mentioned restrictions. For instance, limited social interaction could have frustrated the need for bonding and contact. The loss of positive reinforcement through activities (e.g., sports clubs and cinemas) could have further threatened the need for pleasure and self-esteem enhancement. In particular, the loss of positive reinforcement can be a major risk factor for depression (*reinforcement theory*; Lewinsohn 1974; Vujanovic et al. 2017). Additionally, the uncontrollability of a situation is often discussed as an etiological factor in the pathogenesis of depression and anxiety *(learned helplessness theory;* Seligman 1972; Trindade et al. 2020).

The risk of developing a mental disorder while facing the burdens of a pandemic varies among individuals. According to the diathesis-stress model (Ingram and Luxton, 2005), the interaction of critical life events (e.g., the COVID-19 pandemic) and individual vulnerability factors (for instance, genetic, socioeconomic status, pre-existing mental disorder) predispose a person to develop psychopathological symptoms. Previous research identified several single risk factors associated with increased levels of depression and anxiety during the COVID-19 pandemic, which could be characterized as sociodemographic, health-related, and pandemic-related risk factors. The sociodemographic risk factors included younger age (Ajduković et al., 2021; Fukase et al., 2021; Georgieva et al., 2021), female gender (Hyland et al., 2020; Özdin and Bayrak Özdin, 2020; Sherman et al., 2020), lower education (Peng et al., 2020), lower income (Fukase et al., 2021; Sherman et al., 2020), not working and student status (Fukase et al., 2021; van der Velden et al., 2020), being single or unmarried (Fukase et al., 2021; Peng et al., 2020), and living alone (Rutland-Lawes et al., 2021). Health-related risk factors refered to poor health status (Ajduković et al., 2021; van der Velden et al., 2020), pre-existing mental disorders (Ajduković et al., 2021; Georgieva et al., 2021; Sherman et al., 2020), or trauma exposure (Lahav, 2020). Pandemic-related factors included reduced income (Fukase et al., 2021; Hyland et al., 2020), high consumption of COVID-19-related news (Ajduković et al., 2021; Georgieva et al., 2021), and less social contact (Sommerlad et al., 2021).

Taken together, there is evidence of several factors that have put an individual at a greater risk of developing depressive or anxiety symptoms during the pandemic. However, profiles of risk factors (i.e., distinct accumulations of single risk factors) have not yet been identified. Pre-COVID-19 studies have already examined mental health risk profiles in different subgroups, such as children and adolescents (Göbel and Cohrdes, 2021; Parra et al., 2006) or older adults living alone (Lee et al., 2021). Göbel & Cohrdes (2021) found four risk profiles (*basic, high, parental*, and *social risk*) in children and adolescents that showed differences in mental health outcomes. Individuals in the *high-risk* profile (i.e., many risk factors across all domains) were more likely to have mental disorders (e.g., depression) than individuals from the other profiles. Parra et al. (2006) identified four risk profiles: *Low risk, socioeconomic disadvantage, peer high-risk,* and *family high-risk*. Individuals in the *family high-risk* profile reported the highest levels of depressive symptoms. Among older people living alone, Lee et al. (2021) found three risk profiles: (1) *high cognitive dysfunction, high loneliness, and low social support* (2) *low psychological risks and high social support* (3) *high depression and high suicidal ideation*. Older people with *low psychological risk and high social support* reported a significantly higher quality of life than the remaining profiles. These studies indicate that risk profiles across different known risk domains provide meaningful information about the mental health of different subgroups.

To our knowledge, this is the first study investigating profiles of risk factors for depressive and anxiety symptoms in the general adult population in Germany during the first phase of the COVID-19 pandemic. Identifying these profiles during a pandemic can be beneficial in several ways. From a clinical perspective, a better understanding of vulnerable groups can help to develop targeted prevention or intervention programs tailored to the needs of these individuals. From a political perspective, this knowledge can help to better align political decisions with the needs of this population group. Especially during a pandemic, this can help allocate resources (e.g., financial aid and support programs) more efficiently and provide targeted support to those most at risk. Therefore, finding profiles of risk factors in pandemics can contribute to improved detection, monitoring, and treatment of mental health problems and ensure that policy decisions are based on scientific evidence.

Therefore, this study aimed to

(i) identify profiles of risk factors in the German adult general population during the first half year of the COVID-19 pandemic, and,
(ii) examine differences between these profiles regarding levels of depressive and anxiety symptoms.

With regard to pre-COVID risk profile studies (Göbel and Cohrdes, 2021; Lee et al., 2021; Parra et al., 2006), we have developed two hypotheses. First, we expected to identify three to four latent profiles that differ in the number and individual constellations of risk factors (H_1). Second, we hypothesized that profiles with higher probabilities of fulfilling the included risk factors report higher levels of depressive and anxiety symptoms than profiles with lower probabilities (H_2).

2. Methods

2.1. Study design and setting

The participants were recruited as part of a pan-European cohort study (ADJUST study) of the European Society for Traumatic Stress Studies (ESTSS; for details, see Lotzin et al. 2020). The ADJUST study longitudinally investigates risk and protective factors, stressors, coping, and symptoms of an adjustment disorder during the COVID-19 pandemic in eleven countries.

2.2. Procedure

We collected the data from the German general population between June and September 2020. The survey was actively advertised via social platforms (e.g., Facebook, Twitter), leisure and interest groups (e.g., bicycle or car clubs), newsletters or organizations (e.g., newsletters of large companies), and advertisements in newspapers and magazines. Study information was also disseminated through universities, different stakeholders, and professional organizations. Interested individuals received an invitation link to the online platform *Limesurvey* (LimeSurvey GmbH, Version 3.22). After providing consent, they could complete an online survey.

2.3. Participants

Data of this study stem from the first wave of assessment. In total, $N = 2245$ German adult participants from the general population were included in this study. Inclusion criteria were (1) at least 18 years of age,

(2) ability to read and write in German, (3) willingness to participate in the study. We only included participants with no missing values in the dependent variables. No a priori sample size calculation was conducted, as this study is a secondary data analysis drawn from the ADJUST study.

2.4. Measures

2.4.1. Risk factors

We included sociodemographic, pandemic-related, and health-related risk factors in our study based on previous COVID-19 research. All risk variables were dichotomized for the analysis (0 = *does not apply,* 1 = *applies*, see Supplement Table S1).

As sociodemographic risk factors, we included age, gender, education, income, working and student status, relationship status, and living situation. Age was recoded into *young age* (≤ 25 years vs. > 25 years). We recoded gender to *female gender (*vs. *male* or *diverse gender)*. For education, the highest level of education was assessed ("What is your highest education?"; 1 = *Less than 6 years of schooling,* 2 = *6–9 years of schooling,* 3 = *10–13 years of schooling,* 4 = *Completed vocational studies,* 5 = *Completed studies*, 6 = *Doctorate*). We recoded this variable to the risk factor *lower education (*≤ 13 years of schooling vs. > 13 years of schooling). As only *n* = 7 participants reported education of fewer than 10 years of schooling, we had to assign people with 10–13 years of schooling to the *lower education* group. Income ("What is your average monthly household income after paying taxes (in Euro)?"; 1 = *Less than €500,* 2 = *€500 to less than €1000,* 3 = *€1000 to less than €2000,* 4 = *€2000 to less than €3000,* 5 = *€3000 to less than €5000,* 6 = *€5000 or more*) was recoded into the variable *lower income* (< €1000 vs. ≥ €1000). Work status ("What is your current training or work situation?"; 1 = *Vocational training/study*, 2 = *Employed part-time*, 3 = *Employed full time, 4* = *Self-employed,* 5 = *Freelancer*, 6 = *Retired,* 7 = *Seeking work*, 8 = *Other*) was recoded into two separate variables: *Not working* (retired or job seeking vs. not retired or job seeking), and *Student or vocational studies status* (vs. not student or vocational studies status). Relationship status (1 = *Single*, 2 = *Temporary relationship(s)*, 3 = *Stable relationship, living separately*, 4 = *Stable relationship, living together*) was recoded into the variable *single* (0 = *No*, 1 = *Yes*). The variable living situation ("Do you live together with other people?"; 0 = *No*, 1 = *Yes*) was recoded into the variable *living alone* (living alone vs. not living alone).

As health-related risk factors, we included health status, pre-existing mental disorders, and trauma exposure. Health status ("How would you describe your current health?"; 1 = *Very good,* 2 = *Good*, 3 = *Satisfactory*, 4 = *Bad,* 5 = *Very bad)* was transformed into *poor health status* (very bad to satisfactory health status vs. good or very good health status). The variable on mental disorders ("Have you ever been diagnosed with a mental disorder, e.g., depressive disorder or anxiety disorder?"; 0 = *No*, 1 = *Yes, but I have recovered*, or 2 = *Yes, I am currently affected*) was recoded into the risk factor *pre-existing previous or current mental disorders (*vs. no mental disorder*)*. Trauma exposure (before or during the pandemic) was measured using two separate questions ("Experienced this kind of event(s) during the Coronavirus pandemic?"; "Experienced this kind of event(s) before the Coronavirus pandemic?"; 0 = *No*, 1 = *Yes*). Since only a few people had already experienced a traumatic event at the beginning of the pandemic, we summarized the items into one variable (*trauma exposure*).

As pandemic-related risk, we included reduced income, COVID-19-related news consumption, and frequency of social contact. The reduced income variable ("Has the coronavirus pandemic reduced your monthly household income?"; 1 = *Yes*, 0 = *No*) was recoded into *loss of income (*vs. no loss of income*)*. News consumption ("How many hours a day do you spend watching, reading, or listening to news or other information about the coronavirus pandemic?", 0 = *I do not watch, read or listen to news about the coronavirus pandemic*, 1 = *Less than 30 min a day*, 2 = *30–60 min a day*, 3 = *1–2 h a day*, 4 = *2–3 h a day*, 5 = *More than 3 h a day*) was recoded into *high news consumption* (consumption of at least 1–2 h a day vs. less than 1–2 h a day). Social contact ("How often do you have (physical) personal contact to loved ones or friends?"; 0 = *I have no personal contact with other people*, 1 = *Less than once a week,* 2 = *Once a week*, 3 = *1–2 times a week*, 4 = *3–6 times a week*, 5 = *Everyday*) was recoded to *low social contact* (less than once a week or no social contact vs. at least once a week).

2.4.2. Depressive symptoms

Depressive symptoms were assessed as the dependent variable using the Patient Health Questionnaire 9 (PHQ-9; Kroenke et al. 2001). The PHQ-9 is a self-report questionnaire and screening tool consisting of nine items based on the Diagnostic and Statistical Manual of Mental Disorders-IV (DSM-IV) criteria for depression. The questionnaire is often used as a brief diagnostic and severity measure in research and clinical context. For each item, people indicated on a scale of 1 to 3 whether this symptom had bothered them in the last two weeks (0 = *not at all*, 1 = *several days*, 2 = *more than half of the days*, 3 = *nearly every day*). A total score (ranging from 0 to 27) can be calculated by summing the item scores to assess the severity of a depressive episode. PHQ-9 scores of 5 to 9 indicate mild depression; 10 to 14 indicate moderate depression; 15 to 19 indicate moderately severe depression, and ≥ 20 indicate severe depression. A cut-off score between 8 and 11 has been recommended to screen for probable depression (Manea et al., 2012).

Empirical studies found strong support for criterion and construct validity as well as reliability (Gilbody et al., 2007; Levis et al., 2019; Sun et al., 2020). A meta-analysis of 14 clinical studies showed high sensitivity (80%) and specificity (92%) for the PHQ-9 across the studies (Gilbody et al., 2007). A more recent meta-analysis (Levis et al., 2019), including 58 studies, reported a sensitivity of 88% and a specificity of 85% for the PHQ-9.

2.4.3. Anxiety symptoms

Anxiety symptoms were assessed as the dependent variable with the GAD-2, a short version of the 7-item Generalized Anxiety Disorder self-report screening scale (GAD-7; Spitzer et al., 2006). The GAD scale is based on the criteria for diagnosing generalized anxiety disorders based on the American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (APA, 2000). The GAD-2 includes the first two items of the GAD-7, which represent the core anxiety symptoms ("feeling nervous, anxious, or on edge" and "not being able to stop or control worrying"). The questionnaire assessed how often (0 = *not at all*, 1 = *several days*, 2 = *more than half of the days*, 3 = *nearly every day*) individuals had experienced anxiety symptoms during the last two weeks. The GAD-2 sum score ranges from 0 to 6; a score ≥ 3 on the GAD-2 has been identified as an acceptable cut-off to identify clinically relevant anxiety symptoms in the general population (Plummer et al., 2016). The GAD-2 was validated in several studies and showed to retain the excellent psychometric properties of the GAD-7 (Sapra et al., 2020). A systematic review and diagnostic meta-analysis reported an acceptable sensitivity of 76% and specificity of 81% for the GAD-2 (Plummer et al., 2016).

2.5. Data analysis

To explore profiles of risk factors, we used latent class analysis (LCA; Lazarsfeld and Henry, 1968) and multiple group analyses (Wald-tests) stepwise.

2.5.1. Step 1: preparing the dataset

First, we prepared the dataset for the analyses using *SPSS* (version 27.0, IBMCorp., Armonk, NY). Following the recommendation by White et al. (2011), we only included cases with non-missing values in the dependent variables (PHQ-9, GAD-2) in the analyses (*N* = 2245). Using imputed outcomes would only add noise to the estimation (White et al., 2011). To meet the prerequisites of the LCA, all risk factor variables were dichotomized (0 = *does not apply*, 1 = *applies*). We then exported the data to *Mplus* (version 7.13, macOS).

2.5.2. Step 2: conducting the LCA

In a second step, an LCA was conducted with *Mplus* to identify latent classes of different risk factors. LCA is an exploratory person-centered statistical method that divides individuals into latent, homogeneous classes based on their response behavior. All model parameters were estimated using Maximum Likelihood estimation and robust standard errors (MLR). Since not all participants reported their income (4.2% were missing), we estimated the missing values using the Full Information ML method, assuming that all missing data were missing at least at random (Akaike, 1987). To avoid local maxima, we used 1000 random sets of initial values in the first step, 250 random sets in the second step of the optimization, and 250 iterations in the initial phase. To determine the optimal number of classes, we used the Bayesian Information Criterion (BIC; Schwarz, 1978), the sample-size adjusted Bayesian Information Criterion (ssBIC; Sclove, 1987), the Lo-Mendell-Rubin adjusted Likelihood Difference test (LMR test; Lo et al., 2001), and the bootstrap likelihood ratio difference test (BLR test; McLachlan and Peel, 2000) as model fit criteria to compare the different models with different class solutions. Nylund et al. (2007) suggest that these goodness-of-fit criteria are the best for determining the optimal class size and classification goodness. The information criteria BIC and ssBIC were used to compare the goodness-of-fit of the competing models, preferring the model with the lowest BIC value. The BIC is based on a log-likelihood function and a penalty term for model complexity to avoid an over-fitted solution. We used the LMR and BLR tests to compare models with increasing numbers of classes to examine which class solution can best represent the data structure. A p-value $\leq .05$ indicates that the estimated model represents the data structure significantly better than a model with k-1 classes (Nylund et al., 2007). Entropy (Ramaswamy et al., 1993) was used as a standardized measure of the accuracy of class assignments. Entropy ≥ 0.80 indicates an acceptable correct assignment probability (Muthén, 2004). Additionally, we considered the interpretability and parsimony of classes as well as a large total sample ($N > 500$; Nylund et al., 2007) and sufficiently large profile sizes ($n > 25$ or $n > 1\%$ of the total sample; Lubke and Neale, 2006). As a further measure of the goodness of the classifications, the estimated mean class assignment probabilities are supposed to be greater than 0.80 (Nylund et al., 2007).

LCA assumes conditional independence of class indicators, i.e., that the indicators are uncorrelated within each class. A violation of the conditional independence assumption can lead to a biased estimation of LCA parameters and model misfit (Lee et al., 2020; Visser and Depaoli, 2022). To account for possible local dependencies, we followed the recommendations of Visser and Depaoli (2022). First, we detected conditional dependencies with MLR estimation. Therefore, we ran the original model with the best fit a second time and examined bivariate residual associations (BVR) based on Pearson test statistic with the 'tech-10′ option in *Mplus*. So far, there is no standard recommendation for when the residual is too high. Asparouhov & Muthén (2015) suggested that BVRs > 30 indicate a violation of the conditional independence assumption and model misfit. We detected two class indicator pairs (*poor health status* and *trauma exposure; pre-existing mental disorders* and *trauma*) with problematic BVRs in the 3-class solution. Second, we modeled conditional dependence with MLR estimation to relax violations of conditional independence. Therefore, we included two class-invariant residual associations in the LCA model. We then compared the results with the non-relaxed LCA 3-class model.

2.5.3. Step 3: conducting a sensitivity analysis

We only included cases with non-missing values ($N = 2245$) in the dependent variables in our study. To ensure that the exclusion of $n = 498$ cases did not lead to substantial changes in the LCA results (e.g., class structure), we ran the LCA with all cases ($N = 2744$) again. Then, we compared it to the results of the LCA model, where we only included cases with non-missing values in the dependent variables ($N = 2245$).

2.5.4. Step 4: automatic BCH approach – multiple group analyses

In the last step, we conducted multiple group analyses to examine differences in depressive and anxiety symptoms among the identified profiles. Therefore, we used the automatic BCH (Bolck et al., 2004) approach in *Mplus*. This procedure uses Wald tests to compare the mean scores of a continuous or categorical distal outcome among different groups. Several simulation studies suggest that this provides robust results also for non-normal distributed variables (Asparouhov and Muthén, 2021; Bakk and Vermunt, 2016). The BCH procedure considers individual uncertainties in profile classification by using observation weights that reflect measurement errors in the latent class variable (Asparouhov and Muthén, 2021).

3. Results

3.1. Sample characteristics

We included $N = 2245$ participants aged 18 to 82 years ($M = 41.07$; $SD = 12.50$) in our study. The sample could be characterized as predominantly female, high-educated with medium to high income on average (Table 1). Average scores for health-related and pandemic-related characteristics are shown in Table 2. The average PHQ-9 score was $M = 6.60$ ($SD = 5.02$), with a prevalence rate of probable depression of 10.7%. The average GAD-2 score was $M = 1.31$ ($SD = 1.56$), with a prevalence rate of a probable anxiety disorder of 17.7%.

3.2. Profiles of risk factors during the COVID-19 pandemic

Model fit indices for a 2- to 5-class solution are presented in Table 3.

Table 1
Sociodemographic characteristics ($N = 2245$).

Characteristics	
Age (in years)	*M (SD)*
Mean	41.07 (12.5)
Range	18–82
Gender	*n* (%)
Male	661 (29.4)
Female	1575 (70.2)
Diverse	9 (0.4)
Education	
< 6 years of schooling	–
6–9 years of schooling	7 (0.3)
10–13 years of schooling	280 (12.5)
Vocational studies	785 (35.0)
Completed studies	1092 (48.6)
Doctorate	81 (3.6)
Income[a]	
Very low (< 500 €)	79 (3.7)
Low (500 < 1000 €)	140 (6.5)
Medium (1000 < 3000 €)	867 (40.3)
High (≥ 3000 €)	1065 (49.5)
Work/training status[b]	
Vocational training or study	348 (15.5)
Employed part-time	612 (27.3)
Employed full-time	1119 (49.8)
Self-employed	85 (3.8)
Freelancer	62 (2.8)
Retired	95 (4.2)
Seeking Work	51 (2.3)
Other	138 (6.1)
Relationship status	
Single	611 (27.2)
Temporary relationship(s)	46 (2.0)
Stable relationship, living separately	193 (8.6)
Stable relationship, living together	1395 (62.1)
Living together with other people?	
Yes	1608 (71.6)
No	637 (28.4)

[a] $n = 2151$.
[b] Multiple answers were possible.

Table 2
Health-related and pandemic-related characteristics ($N = 2245$).

Characteristics	n (%)
Current health status	
Very good	765 (34.1)
Good	1014 (45.2)
Satisfactory	376 (16.7)
Bad	81 (3.6)
Very bad	9 (0.4)
Diagnosis of mental disorder	
No	1716 (76.4)
Yes, recovered	348 (15.5)
Yes, currently affected	181 (8.1)
Trauma exposure	
No	1447 (64.45)
Yes	798 (35.55)
Reduced income	
No	1372 (61.1)
Yes	873 (38.9)
Pandemic-related news consumption	
I do not watch, read or listen to news	101 (4.5)
< 30 min a day	1238 (55.1)
30–60 min a day	679 (30.2)
1–2 h a day	165 (7.3)
2–3 h a day	47 (2.1)
> 3 h a day	15 (0.7)
Physical face-to-face contact	
No face-to-face contact	51 (2.3)
< Once a week	492 (21.9)
Once a week	385 (17.1)
1–2 times a week	778 (34.7)
3–6 times a week	391 (17.4)
Everyday	148 (6.6)

Notes. Reduced income = Reduced monthly household income due to the COVID-19 pandemic. News consumption = Hours a day watching, reading, or listening to the news or other information about the COVID-19 pandemic. Physical face-to-face contact = Frequency of face-to-face contact to loved ones and friends.

Table 3
Model fit indices of profiles of risk factors during the COVID-19 pandemic ($N = 2245$).

Class	Log-likelihood	BIC	ssBIC	LMR test *p*-value	BLR test *p*-value	Entropy
2	−13831.648	27887.07	27794.94	<.001	<.001	0.951
3	**−13426.089**	**27191.70**	**27051.91**	**<.001**	**<.001**	**0.883**
4	−13350.447	27156.17	26968.71	.003	<.001	0.710
5	−13302.571	27176.16	26941.05	.146	<.001	0.728

Notes. Model fit indices for the favored model are in bold. BIC, Bayesian Information Criterion. ssBIC, sample-size adjusted Bayesian Information Criterion. LMR, Lo-Mendell-Rubin adjusted likelihood ratio. BLR, Bootstrapped Likelihood Ratio.

The sensitivity analysis (Supplement Table S2) did not reveal any differences in the results when only including cases with non-missing values in the dependent variables ($N = 2245$) vs. all cases ($N = 2744$). Thus, we assumed that only using cases with non-missing values in the dependent variables would not bias our LCA results.

Based on the BIC and ssBIC values, a 3- or 4-class solution should be preferred. The BIC value declined with an increasing number of classes until the 4-class solution. The 5-class solution had a higher BIC value than the 4-class solution, indicating a lower goodness-of-fit for the 5-class solution. The LMR test revealed a significantly better representation of the data structure using the 4-class compared with a 3-class solution ($p = .003$), but no significant difference between the 4-class and 5-class solution ($p = .146$). However, the BLR test remained significant ($p < .001$). Considering the model quality, the 3-class model showed better entropy (≥ 0.8) and average class assignment probabilities for all classes (> 0.90; Nylund et al., 2007) than the 4-class model. Furthermore, class sizes for the 3-class solution were sufficiently large (all $n > 200$; Lubke and Neale, 2006). Taking into account statistical information measures, entropy, parsimony, and interpretability of the classes, the 3-class solution was to be favored.

Table 4 shows the comparison between the 3-class LCA model and the 3-class relaxed LCA (residual associations) model, which considers conditional dependencies. The 3-class relaxed LCA model showed similar results to the 3-class LCA model, with minor differences in class sizes and model fit parameters. The 3-class relaxed LCA model had a slightly better model fit (i.e., lower ssBIC value) than the 3-class LCA model. We decided to use the 3-class relaxed LCA model in the following.

Several risk factors discriminated well (young age, low education, low income, student status, being single, living alone) or moderately (mental disorder, trauma) between the profiles (see Fig. 1). Class 1 ($n = 262$; 11.7%) was representative of individuals with high probabilities of exposure to five out of eight sociodemographic risk factors (i.e., young age, female gender, low education and income, student status). Therefore, this class was labeled *high sociodemographic risk* profile. Class 2 ($n = 404$; 18.0%) characterized individuals with high probabilities of exposure to two out of eight sociodemographic risk factors (i.e., being single, living alone) and two out of three moderate health-related (i.e., pre-existing mental disorder, trauma) risk factors. As both sociodemographic risk factors contained a social component, we labeled this class *high social and moderate health-related risk* profile. Class 3 ($n = 1579$; 70.3%) was composed of individuals with a low probability of nearly all risk factors. We labeled this class *low general risk* profile.

3.3. Relationships between profiles of risk factors, depressive, and anxiety symptoms

The mean scores of depressive and anxiety symptoms for the three identified risk profiles are shown in Table 5. Individuals in the *high sociodemographic risk* profile descriptively reported the highest levels of depressive and anxiety symptoms. Individuals in the *high social and moderate health-related risk* profile had the second highest symptom levels, while those in the *low general risk* profile had the lowest scores. Multiple group analyses revealed statistically significant differences in depressive ($\chi^2 = 126.36$, $p < .001$) and anxiety symptoms ($\chi^2 = 67.52$, $p < .001$) among the three profiles (Supplement Table S3). These differences existed between all profiles for depressive and anxiety symptoms (Table 5).

4. Discussion

This study investigated profiles of risk factors for depressive and

Table 4
Comparison of model fit indices and class prevalences of profiles of risk factors for 3-class LCA model vs. LCA residual associations model ($N = 2245$).

	3-class LCA model	3-class relaxed LCA model
Model fit		
Log-likelihood	−13426.089	−13381.522
BIC	27191.70	27118.00
ssBIC	27051.91	26971.85
LMR test *p*-value	<.001	<.001
BLR test *p*-value	<.001	<.001
Entropy	0.883	0.882
Class prevalences		
Class 1	0.117	0.117
Class 2	0.182	0.180
Class 3	0.701	0.703

Notes. BIC, Bayesian Information Criterion. ssBIC, sample-size adjusted Bayesian Information Criterion. LMR, Lo-Mendell-Rubin adjusted likelihood ratio. BLR, Bootstrapped Likelihood Ratio.

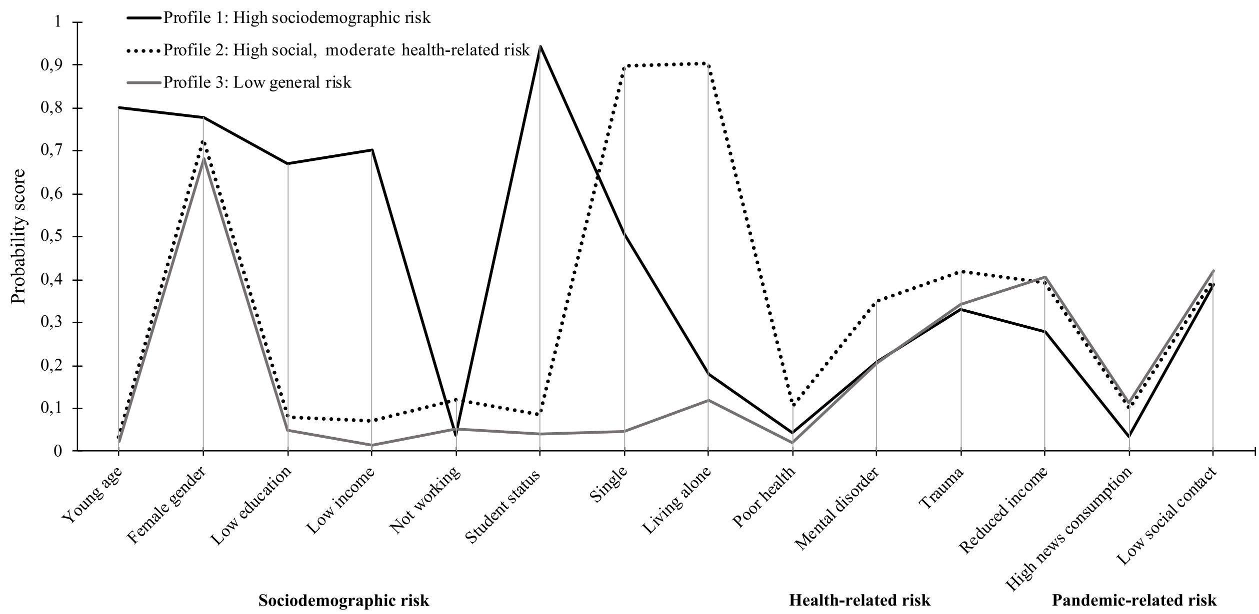

Fig. 1. Profiles of risk factors during the COVID-19 pandemic in the German general population.
Notes. Young age: ≤ 25 years. Low education: ≤ 13 years schooling. Low income: < €1000 net household income per month. Poor health: self-reported very bad to satisfactory health status. Mental disorder: Previous or current mental disorder diagnosis. Trauma: Exposure to a traumatic event before or during the pandemic. Reduced income due to the COVID-19 pandemic. High news consumption: ≥ 1–2 h a day. Low social contact: ≤ once a week or no social contact.

Table 5
Multiple group analyses between the profiles regarding depressive and anxiety symptoms using the BCH approach.

	Profile 1 *M* (*SE*)	Profile 2 *M* (*SE*)	Profile 3 *M* (*SE*)	Pairwise comparisons
PHQ-9 (depression)	9.65 (0.36)	7.69 (0.28)	5.75 (0.12)	1 > 2 > 3
GAD-2 (generalized anxiety)	1.96 (0.11)	1.61 (0.09)	1.11 (0.04)	1 > 2 > 3

Notes. Profile 1: *High sociodemographic risk*. Profile 2: *High social and moderate health-related risk*. Profile 3: *Low general risk*. PHQ-9: Patient Health Questionnaire 9. GAD-2: Generalized Anxiety Disorder self-report screening scale. Differences were analysed using Wald tests. > indicates that one profile has a significantly ($p < .05$) higher value than another profile.

anxiety symptoms during the early phase of the COVID-19 pandemic in Germany. We found three profiles of risk factors in the German adult general population, which is consistent with our previously developed hypothesis. Individuals in these profiles significantly differed in symptom levels of depression and anxiety. The identification of subgroups of individuals with distinct constellations of risk factors could help to develop and evaluate targeted prevention and intervention programs for pandemics.

4.1. Profiles of risk factors and differences in depressive and anxiety symptoms

4.1.1. Profile 1: high sociodemographic risk profile

First, we identified a profile with high probabilities for multiple sociodemographic risk factors (female gender, young age, lower education and income, student status). Individuals in Profile 1 (*high sociodemographic risk*, 11.7%) reported the highest levels of depressive and anxiety symptoms during the COVID-19 pandemic compared with the other profiles. On average, the reported depressive symptoms (PHQ-9) correspond to a mild-to-moderate depression. The average anxiety score (GAD-2) did not exceed the threshold for clinically relevant anxiety. However, anxiety symptoms were significantly higher than in the remaining profiles. To conclude, individuals who were predominantly female, young, and had a student status, low education, and income might have been at the highest risk of developing depressive and anxiety symptoms during the pandemic. This confirms our hypothesis that individuals with high probabilities of fulfilling multiple risk factors report the highest levels of depressive and anxiety symptoms (H_2).

These findings are consistent with prior research investigating the impact of sociodemographic status on mental health (e.g., Santomauro et al., 2021). Women reported higher levels of distress, depression, and anxiety symptoms before (Bretschneider et al., 2018; McLean et al., 2011) and during the pandemic (Dragan et al., 2021; Rossi et al., 2020) compared to men. A possible explanation could be that women are more likely to be exposed to stressful situations (e.g., balancing childcare and work), resulting in higher symptoms of depression and anxiety. This approach refers to the *differential exposure hypothesis.* An opposite assumption (*differential vulnerability hypothesis*) is, that women react more strongly to stressors than men (Day and Livingstone, 2003; Rosenfield and Mouzon, 2013; Roxburgh, 1996). Based on our findings, we cannot explain why the profile with the highest probability of being female had the highest symptom levels. Nevertheless, our results are consistent with the common consensus that women are at a higher risk for depressive and anxiety symptoms in general (e.g., Bretschneider et al., 2018) and during (e.g., Dragan et al., 2021) the pandemic. However, as women were overrepresented in our sample, the probability of female gender in Profile 1 was only about ten percent higher than in the other profiles. The disproportionate representation of women in our study may be attributed to their greater willingness to participate in scientific surveys compared to men (Galea and Tracy, 2007).

In addition to being female, the profile had a high probability of a young age (i.e., under 25 years) and being a student. This agrees with an international meta-regression (Santomauro et al., 2021), which reported elevated prevalences of depressive and anxiety disorders during COVID-19 among women and young people. Even though the young population is one of the least vulnerable groups to a COVID-19 infection from a medical perspective, they seem to be most affected by the pandemic on a psychological level. Several studies support this assumption as they found increased levels of depression and anxiety (Varma et al., 2021; Wang et al., 2021), substance use (Horigian et al., 2021), and suicidal ideation (Shobhana and Raviraj, 2022) in young people and students during the pandemic. A reason for these findings could be that young people and students were drastically affected by the restrictions during the pandemic. Due to the closure of universities, students had to study from home, which could have led to reduced peer contact and social activities. Working students (e.g., in gastronomy) might have lost their job, which in turn could result in an additional financial burden. Moreover, young people are more likely to become unemployed than older people during and after an economic crisis (Bell and Blanchflower, 2011). It has been shown that financial distress among younger adults was associated with poorer depression and anxiety outcomes (Varma et al., 2021). Whereas older people are generally thought to be more at risk for public health emergencies (Cloyd and Dyer, 2010; Lamb et al., 2008), our findings underline that younger adults and students were most vulnerable regarding mental health during the COVID-19 pandemic.

Moreover, the profile had a high probability of low income. This reflects the financial burden of younger people and students during the pandemic. There is evidence of bidirectional causal relationships between poverty and mental disorders (Ridley et al., 2020). Low income and reduced income can lead to increased worry and insecurity and worsen mental health. In turn, mental disorders worsen economic outcomes, for example, through lower work productivity. Jernslett et al. (2022) found an association between difficult housing conditions and depression, which might be mediated by low income. In sum, public health crises, such as the COVID-19 pandemic, tend to disproportionately affect those people living in poverty (Ridley et al., 2020). However, it is unclear whether low income also reflected poverty in our study. Especially, students and young people often receive financial support from their parents or the state. Future studies might consider other forms of financial support to understand the impact of socioeconomic status on mental health.

4.1.2. High social and moderate health-related risk profile

Second, we found a profile with high probabilities for two sociodemographic risk factors (being single, living alone) and moderate probabilities for health-related risk factors (pre-existing mental disorder, trauma). Individuals in Profile 2 (*high social and moderate health-related risk, 18.0%*) had the second highest levels of depressive and anxiety symptoms. They reported significantly fewer symptoms than people in the sociodemographic risk profile but more symptoms than individuals with general low risk. The average depression score could still be interpreted as mild-to-moderate depression (PHQ-9 $>$ 5), whereas the anxiety score did not exceed the threshold for clinically relevant anxiety. In sum, predominantly single individuals who lived alone and had a moderate probability of trauma and a pre-existing mental disorder had a slightly increased risk for depressive and anxiety symptoms during the pandemic.

Several studies found associations between being single and living alone with higher levels of depressive and anxiety symptoms during the COVID-19 pandemic (e.g., Benke et al. 2020; Fancourt et al. 2020). A German study reported higher depressive (but not anxiety) symptoms among single individuals compared with those in a relationship (Benke et al., 2020). Pre-COVID-19 research indicated that an intimate relationship can serve as a buffer against stressors and burdens and allow for dyadic coping during stressful times (Revenson et al., 2005). Empirical studies found associations between dyadic coping and higher well-being and fewer psychological problems (Revenson et al., 2005). From a neurophysiological perspective, studies found lower general stress levels (measured with blood pressure) in individuals in a relationship compared with single ones (Sisca and Walsh, 1985). Despite the beneficial factors, being in a relationship might also bring along some risk factors, such as intimate partner violence or contagion of negative feelings. However, we assume that a well-functioning relationship (compared to being single) was more beneficial during the difficult times of isolation during the COVID-19 pandemic.

Research on living alone (compared to living with others) before and during the pandemic suggested associations with higher levels of depression, anxiety, and other mental disorders (Fancourt et al., 2020; Jacob et al., 2019; Robb et al., 2020). However, the results are inconsistent. García-Fernández et al. (2021) found elevated symptoms of anxiety, but not depression, in women living alone. Robb et al. (2020) found higher levels of depression and anxiety among older people living alone, especially among men. In a Dutch sample, Hendriksen et al. (2021) found that both people living alone and those living with others reported a decrease in mood (i.e., higher levels of stress, depression, anxiety and fatigue) during the lockdown. However, individuals living alone showed significantly greater increases in feelings of loneliness. Kowal et al. (2020) analyzed data from 26 countries (Europe, the USA, South America, and Asia) and did not find higher levels of stress among people living alone. The authors concluded that individuals in that sample might prefer to live alone and still had a high connection with non-household friends or relatives. However, the study did not assess symptoms of depression or anxiety. Interestingly, individuals with *high sociodemographic risk* (Profile 1) had a low probability of living alone but significantly higher symptom levels than those individuals with a high likelihood of living alone (Profile 2). There might be two possible explanations: First, the other risk factors in Profile 1 had a strong impact that could not be mitigated by living with other people, or second living with other people was not only beneficial concerning mental health. During the lockdown, living with others could also be stressful, especially with limited space or when working from home. However, individuals with *low general risk* (Profile 3) had the lowest probability of living alone and the lowest symptom levels of depression and anxiety. This could imply that the positive effect of living with others on mental health depended on the circumstances (e.g., the size of living space). Nevertheless, during a pandemic with periods of social isolation and physical distancing, living alone could have been an important risk factor for loneliness and thus for symptoms of depression or anxiety.

Besides being single and living alone, individuals in this profile had a slightly higher probability of trauma exposure and a pre-existing (previous or current) mental disorder than individuals in the other profiles. Interestingly, studies also indicated that people who live alone are more likely to have a mental disorder (Jacob et al., 2019; Tamminen et al., 2019), which would be consistent with this profile. Furthermore, trauma and mental disorders can also go along. According to a German representative study (Maercker et al., 2008), around 12.0% of all trauma survivors develop posttraumatic stress disorder (PTSD). Especially, rape (37.5%), child abuse (35.3%), and life-threatening illnesses (23.4%) are associated with the highest risk of developing PTSD (Maercker et al., 2008). In addition, McKay et al. (2021) reported in a systematic review that trauma in childhood or adolescence is associated with a psychiatric disorder in adulthood (e.g., depression or anxiety).

During the COVID-19 pandemic, several cross-sectional studies reported elevated levels of depression and anxiety among individuals who experienced previous traumatic events or adverse childhood experiences compared to non-exposed individuals (Chi et al., 2020; Lahav, 2020; Tsur and Abu-Raiya, 2020). These findings correspond to the *stress sensitisation hypothesis* (Hammen, 2015), which assumes that early traumatic experiences lead to stress sensitization, making an individual more reactive to later stressors and vulnerable to adult mental disorders. Perhaps neurophysiological alterations after trauma exposure mediate this relationship (Bremner, 2006). However, Lahav (2020) found this association mainly among those individuals who experience continuous traumatic stress. Since we did not collect data on the type and time of the trauma and whether it is still ongoing or not, we cannot draw any conclusions about this. Nevertheless, we assume that trauma exposure increases one's vulnerability when facing additional burdens, such as the COVID-19 pandemic.

In addition, previous studies reported that individuals with pre-existing mental disorders were more susceptible to stress, depression, and anxiety during the COVID-19 pandemic (for review, see Neelam et al. 2021). Georgieva et al. (2021) found a 2.58-fold higher risk of depression and a 2.87-fold higher risk of GAD in individuals with previous mental disorders. A German longitudinal study indicated that especially individuals with previous anxiety disorders experienced enhanced symptoms of depression and anxiety in the first three months of the pandemic (Bendau et al., 2021). There might be various explanations for why people with a mental health diagnosis reported increased symptoms of depression and anxiety during the pandemic. For instance, it could stem from an increased tendency to ruminate or worry (O'Connor et al., 2022) or a lack of adaptive and use of maladaptive coping (Holt-Gosselin et al., 2021) to manage the burdens of COVID-19. Furthermore, the onset of a mental disorder might increase the individual sensitivity to subsequent stressful experiences (Husky et al., 2009). Additionally, individuals with a current mental disorder may have had difficulties attending appointments (e.g., psychotherapy sessions) or receiving support from the healthcare system, especially at the beginning of the pandemic, due to constraints such as physical distance. These difficulties may have in turn worsened symptoms of depression and/or anxiety.

4.1.3. Low general risk profile

Third, we detected a profile with general low probabilities for nearly all risk factors. Individuals in Profile 3 (*low general risk, 70.1%*) had the lowest levels of depressive and anxiety symptoms of all profiles. However, the average score of depressive symptoms could still be interpreted as mild depression (PHQ-9 > 5). Similar to the other profiles, the mean anxiety score for this profile was below the cut-off for a potential anxiety disorder. Since meta-analyses found prevalences of depression and anxiety up to 30% during the pandemic (e.g., de Sousa et al. 2021), this would fit a low general risk profile of about 70%. Even though individuals had low probabilities for almost all risk factors, some factors showed similar moderate probabilities among all profiles. This included the risk factors *female gender, reduced income*, and *low social contact.* Thus, pandemic-specific risk factors (reduced income, low social contact) in particular, did not show good discrimination between the profiles. This could explain why individuals with *low general risk* still had slightly increased levels of depressive symptoms. Two longitudinal studies from the US and Israel reported associations between abrupt loss of income and greater depressive and anxiety symptoms (Hertz-Palmor et al., 2021). This link was stronger for depressive than for anxiety symptoms, which is consistent with our findings. However, we assume that wealthier individuals had a financial buffer (e.g., savings) against income loss and were not affected as much as people with lower income (such as individuals in Profile 1).

Regarding low social contact, a longitudinal UK study (Sommerlad et al., 2021) found a link between more face-to-face contact and fewer depressive symptoms during the lockdown. Specifically, daily face-to-face contact was associated with a 29% lower risk of depression (Sommerlad et al., 2021).

5. Strengths and limitations

Our study has several strengths, including the large sample size, the use of well-validated instruments, and the consideration of risk patterns instead of single risk factors. Nevertheless, some limitations must be considered. First, the data stem from a cross-sectional study, so no causal conclusions between profiles of risk factors and depressive or anxiety symptoms can be drawn. Longitudinal studies are required to analyze this relationship. Second, we used a non-representative sample, overrepresenting women and individuals with high education, income, and internet access. Due to overrepresentation and selection bias, our results cannot be generalized to the German general population. Third, we used an exploratory statistical technique (LCA) to identify latent homogeneous groups within the sample. Not all statistical model fit indices pointed to a 3-class solution. Future studies using LCA should replicate these profiles to test the stability of our results. However, we used the automatic BCH method to consider inaccuracies in profile classifications when examining differences in depression and anxiety between the profiles. Fourth, we had to dichotomize the risk factors for the LCA, which reduced the information richness of the data. Choosing a different recoding might have led to different results. Additionally, due to a lack of data, we had to summarize several variables (e.g., trauma before or during the pandemic to *trauma*), so the results give a general rather than a specific picture. Because of the highly educated sample, the risk factor *lower education* comprised all individuals with at least 13 years of schooling and therefore also young people who were still in their (vocational) studies. This should be considered when interpreting this risk factor. Furthermore, the probabilities for some risk factors (such as female gender, reduced income, not working, low social contact, poor health status) did not substantially differ between the profiles. Finally, we only included a limited number of risk factors for depression and anxiety in the LCA. There might be more risk factors (e.g., genetics) that explain variations in the development of depressive and anxiety symptoms. Future studies could include more evidence-based risk factors in the LCA to analyze how far this will change the class structure.

6. Conclusion

To our knowledge, this is the first study examining profiles of risk factors for symptoms of depression and anxiety in the German general population during the COVID-19 pandemic. Individuals with *high sociodemographic risk* showed the highest levels of depressive and anxiety symptoms, followed by individuals with *high social and moderate health-related risk* and *low general risk*. Our findings imply that young people and students were particularly at risk of developing depression or anxiety symptoms during the COVID-19 pandemic. Longitudinal studies with representative samples are required to investigate this relationship in more detail. For example, it would be interesting to examine the stability of these profiles throughout the pandemic and the impact of changes in the pandemic situation (e.g., higher incidences, vaccination rate, getting used to the circumstances) on those.

Young people and students in particular received little attention during the pandemic in Germany, as the government focused more on protecting the elderly, implementing measures to contain the virus, and providing rapid economic support to companies and self-employed people (BMWK, 2022; Schweiger, 2022). Our findings could inform the German government for future pandemic situations that more attention needs to be paid to young people and low-income students, either through rapid financial help or psychosocial prevention and support programs.

Ethics, consent, and permissions

The ADJUST study was registered in a study registry before its start (OSF registry, doi: 10.17605/OSF.IO/8XHYG). We obtained ethical approval of the study for the German sample from the Local Psychological Ethics Committee at the center for Psychosocial Medicine, LPEK-0149. All participants provided informed consent before taking part in the study. Participants were informed that they were under no obligation to participate and that they could withdraw at any time from the study without consequences.

Data protection and quality assurance

The dataset for the data analysis was stored on a server of the coordinating site (Center for Interdisciplinary Addiction Research, CIAR, University of Hamburg). Data handling followed the EU General Data Protection Regulation (DSGVO); data will be stored for at least 10 years.

Data availability statement

The detailed sociodemographic information of the dataset does not fully protect the anonymity of the respondents. For this reason, the entire dataset cannot be made publicly available. However, excerpts of the data on a higher aggregation level can be provided upon justified request by the last author.

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Author statement

L.K. and A.L. contributed to the design of this secondary analysis. A. L. designed the ADJUST study from which the data were drawn, in cooperation with all members of the ADJUST consortium. A.L. coordinated the data collection. L.K. was responsible for data cleaning and management with the help of L.v.H. L.K. conducted the data analysis and drafted the manuscript. All authors substantially contributed to the interpretation of the data for this work, revised the manuscript and approved the final version.

Declaration of Competing Interest

The authors declare that the research was conducted in the absence of any commercial or financial interests that could be perceived as a potential conflict of interest.

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Supplementary materials

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