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Published online: 24 Jun 2022.

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# Resilience patterns of Swiss adolescents before and during the COVID-19 pandemic: a latent transition analysis

Clarissa Janousch [a], Frederick Anyan [b], Roxanna Morote [b,c] and Odin Hjemdal [b]

[a]Institute for Research and Development, School of Education, University of Applied Sciences and Arts Northwestern Switzerland, Brugg-Windisch, Switzerland; [b]Department of Psychology, Norwegian University of Science and Technology, Trondheim, Norway; [c]Department of Psychology, Catholic University of Peru, San Miguel, Peru

**ABSTRACT**

This study investigated resilience patterns and predictors of these patterns (i.e. gender and migration background) among Swiss early adolescents in times of COVID-19. A total of 317 pupils participated at two time points. We conducted two separate latent class analyses and a latent transition analysis using mental health issues and protective factors as indicators. The results revealed three groups: resilient (high mental health issues, high protective factors), nonresilient (high mental health issues, low protective factors), and untroubled (low mental health issues, high protective factors). The resilient group was the most stable (91% stability), whereas the untroubled was the least stable (69% stability). Boys were more likely to be part of the untroubled group than the other groups at the second time point. Gender at the first time point and migration background at both time points were nonsignificant as predictors. Findings highlight the importance of group-specific research, health promotion, and interventions.

## Background

In the field of psychology, resilience researchers have established a substantive body of knowledge (Masten, 2014; Rutter, 2012). The interest in resilience as a possible method of identifying protective factors in order to prevent psychological disorders such as anxiety or depression especially drove this research area (Hjemdal, 2007). However, resilience processes are highly heterogeneous (Ungar, 2021) and operate throughout the life span (Masten, 2014; Rutter, 2012). Therefore, this paper represents our attempt to investigate resilience profiles in Swiss adolescents across time by conducting a latent transition analysis (LTA) using protective factors (Personal Competence, Social Competence, Structured Style, Social Resources, and Family Cohesion) and levels of mental health issues (anxiety and depression).

Even though resilience is characterized by definitional ambiguity, there is fundamental agreement across different fields that resilience can be broadly defined as processes of adapting well to disturbances that threaten a system's development, function, or viability (Masten, 2014). This definition is based on three core components of the concept of resilience: first, certain adversities, risks, or vulnerabilities; second, protective factors that supersede these adversities, risks, or vulnerabilities; and third, positive adaption despite facing these adversities, risks, or vulnerabilities (Fletcher & Sarkar, 2013; Masten, 2001; Windle et al., 2011). Most importantly, resilience is not a state but a highly dynamic process characterized by fluctuating protective factors that are being used to

**CONTACT** Clarissa Janousch  clarissa.janousch@fhnw.ch

one's advantage to buffer risks in different circumstances and at different points in time (Stainton et al., 2019). These protective factors are often separated into 'assets' and 'resources' (Fergus & Zimmerman, 2005). Whereas assets refer to intrapersonal factors such as competences and skills, resources refer to interpersonal factors such as nurturing relationships with family and friends and access to health or educational systems (Graber et al., 2016; Rutter, 2012). The latter are especially crucial to children and adolescents for their personal (Herbers et al., 2014; Pieloch et al., 2016) and neurocognitive development (Baker et al., 2012). Furthermore, resilience is an interactive process, and fostering protective factors is central to promoting mental health (Liebenberg & Joubert, 2020).

During early adolescence, a highly vulnerable period associated with a number of biological, psychological, physical, and social changes, the pubertal transition can cause an increased risk of mental health issues (Steinberg, 2020). International studies have shown psychological disorders such as anxiety and depression already occur during infancy (1–5 years) and anxiety is most prevalent during childhood (Schweizerisches Gesundheitsobservatorium [Obsan], 2020). Over 24% of 6- to 9-year-old children show anxiety symptoms, and this disorder affects about 10%–24% of early adolescents (10–13 years). At the same time, major depression is especially prevalent during adolescence (about 13.5%) but also occurs in about 1%–10% of all children and early adolescents.

The Zurich Epidemiological Study of Child and Adolescent Psychopathology (Steinhausen et al., 1998) presented a similar picture for Swiss adolescents. The study confirmed international findings demonstrating high levels of depression and anxiety among children and adolescents. About 25.4% of 10–13-year-olds were affected by a psychological disorder, most commonly anxiety disorders (11.4% of 6–17-year-old children and adolescents). Interestingly, the study also confirmed previous studies (e.g. Costello et al., 2003) indicating that in general, prevalence decreases during adolescence. Nonetheless, these findings are highly dependent on the subject being investigated. Whereas, for example, ADHD and disruptive behaviour decrease during adolescence, levels of depressions and anxiety tend to increase depending on the sample investigated.

However, these mental health issues are not only age-related but also gender related. According to results of the Health Behaviour in School-Aged Children Survey in Europe and Canada (Inchley et al., 2020), comprised of data on 227,441 adolescents between 11 and 15 years of age in 45 countries and regions, significant differences could be detected between girls and boys regarding their mental health. Boys reported higher mental well-being levels than girls across almost all countries and regions. An epidemiological study from the United States focusing on depression and anxiety during puberty among girls and boys found that in general, depression levels increased by early adolescence and were high by the end of puberty, especially among girls (Glied & Pine, 2002). Additionally, depression levels were higher for girls than for boys. The results were similar for anxiety, although boys showed higher levels of anxiety than girls at ages 10 to 13.

The possible adverse effects of migration on mental health have also been well established and have to be taken into account when analysing resilience patterns in adolescents. These effects might be the result of exposure to traumatic events, impoverishment, and daily stressors (Gambaro et al., 2020; Siriwardhana et al., 2014) or difficulties in adapting to new and strange environments (Ahmed & Bhugra, 2007). Migration processes can be accompanied by major life changes or challenges that can cause stress and thus require immigrants to have immense coping skills and protective factors to be able to adjust to these challenges (Bustamante et al., 2017).

Furthermore, it is crucial to take the current situation of the COVID-19 pandemic into account. According to UNESCO, restricted access to education has affected about 87% of the world's students (i.e. more than 1,500,000,000 children and adolescents in 165 countries). Switzerland was among the 10 countries worldwide with the highest per capita rates of COVID-19 infections (Salathé et al., 2020). Between 16 March and 26 April 2020, Switzerland experienced its first lockdown ever (Nivette et al., 2021), including hygiene and social distancing rules, the prohibition of social gatherings of more than five people, and requirement for people to stay home whenever possible (Federal Office of Public Health, 2020; World Health Organization [WHO], 2020). Schools had to close down on 16 March 2020, and students were taught in a distance learning setting until 11 May 2020. These

announcements came with very short notice, so teachers, students, and parents were mostly unprepared for this situation (Tomasik et al., 2021). Some schools even stayed closed until the end of school year (July 2020). Even after the lockdown, a 'slowdown' was implemented, with mandatory nationwide wearing of face masks in public buildings such as schools, no gatherings of more than 15 people, and recommended home-office work during the summer and beginning of autumn (Moser et al., 2021). Therefore, the pandemic might present tremendous challenges to students' mental health. Because of the novel environmental factor, these impacts remain highly uncertain.

An early study from China of 8,079 adolescents (aged 12–18 years) reported an increased prevalence of anxiety and depression levels associated with the pandemic (S.-J. Zhou et al., 2020). These findings were partially supported by a Swiss study investigating adolescents aged 12–17 (Mohler-Kuo et al., 2021). One third of the 1,146 children and adolescents met the criteria for one mental health problem (anxiety, depression, ADHD- or ODD-related symptoms) during the first lockdown in Switzerland. However, these levels, with the exception of depression, remained similar to those before the pandemic. Among males, depression symptoms increased slightly. In general, girls reported more mental health issues than boys during the lockdown. The depression rates were 9.7% of girls and 4.6% of boys, and the anxiety rates were 13.6% of girls and 12.5% of boys. These findings were lower than the rates reported in the Chinese study and in recent systematic reviews where they ranged from 18.9% to 37.4% for anxiety and 22.6% to 43.7% for depression (Nearchou et al., 2020; Panda et al., 2021). Nevertheless, it is important to mention the different measurements that have been used in all studies and might have led to such divergent results.

These findings indicate one further essential aspect of resilience: its stability. Even though the pandemic as an extraordinary time might have detrimental impact on adolescents' mental health, a notable number of children and adolescents appear to remain healthy. A relatively steady course of good functioning despite facing adversities has often captured the attention of pioneering resilience scientists in the past. The so-called 'invulnerable' or 'stress resistant' children may have led to a misleading perception that resilience is rare and highly fluctuating. However, research has shown that powerful protective factors help mitigate risks and operate on behalf of children facing adversities and risks; thus, resilience can rather be described as an 'ordinary magic' (Masten, 2001, 2014).

Following these insights, pathways of resilience are dependent on several determinants, such as protective factors and risk factors. Individuals will fluctuate regarding their levels of protective factors across areas and over their life spans (Luthar et al., 2000), and mental health may change quickly, especially during early adolescence and extraordinary times such as a pandemic. Hence, the fundamental principles of the concept that resilience and its components might fluctuate across times and contexts and that there might be gender- and migration background-related differences demonstrate the importance of analysing resilience across time.

In order to take the possibly fluctuating and highly individual resilience process into consideration, we used latent class analysis (LCA) and LTA for a person-centred approach to identifying groups based on similar response patterns (Clogg, 1995; Lanza et al., 2012; McCutcheon, 1987). According to Masten and Barnes (2018), in resilience research, person-centred methods acknowledge the person as a whole unit of interest and thus support the idea of this heterogeneous dynamic process with fluctuating factors.

Investigations of protective factors and mental health issues (across time) have resulted in ambiguous findings when conducted with person-centred approaches. These findings have differed not only quantitatively but also qualitatively depending on the samples and how resilience has been operationalized. In a recent study from China, researchers conducted an LTA with the protective factors of life satisfaction and self-esteem and disorders, such as depression and anxiety and identified three distinctive groups among early adolescents (J. Zhou et al., 2020): flourishing youth (i.e. high protective factors, low mental health issues), vulnerable youth (i.e. low protective factors, low mental health issues), and troubled youth (i.e. low protective factors, high mental health issues). Other longitudinal studies using a dual-factor model of mental health (including positive and

negative aspects of mental health such as protective factors and mental health issues) have found four transition patterns within their frameworks (i.e. flourishing, troubled, vulnerable, and symptomatic but content) for adolescents (e.g. Kelly et al., 2012; Xiong et al., 2017). The four profiles were almost identically replicated by Moore et al. (2019): completely mentally healthy, moderately mentally healthy, symptomatic but content, and troubled.

These four studies have in common that they have investigated adolescents across time, suggesting a three- or four-class solution and finding similar stabilities across the classes. In these studies, the flourishing students were most likely to remain in their group (up to 93%), whereas the vulnerable (Kelly et al., 2012; J. Zhou et al., 2020) or troubled (Moore et al., 2019; Xiong et al., 2017) classes were the least stable (down to 24%). In general, these adolescents tended to progress towards the flourishing class instead of regressing towards the troubled groups over time. Nevertheless, deriving conclusions based on these findings is difficult because of the person-centred approach, which might be highly dependent on the sample, and because of the contextual nature of resilience.

Therefore, the aim of this study was to investigate quantitative and qualitative changes in resilience classes. First, when conducting separate LCAs, we wanted to find the ideal number of groups for both time points. Based on previous findings, we expected to find three or four resilience classes (Hypothesis 1; Kelly et al., 2012; Moore et al., 2019; Xiong et al., 2017; J. Zhou et al., 2020). Second, we were interested in the quantitative and qualitative changes representing the classes' stability over the two time points (Wave 1 and Wave 2). In line with previous research, we hypothesized that there would be interindividual differences in resilience classes because resilience is a dynamic construct that may fluctuate over a time period of 1 school year (Hypothesis 2; Kelly et al., 2012; Masten, 2014; Moore et al., 2019; Xiong et al., 2017; J. Zhou et al., 2020). Third, we investigated the class membership of these adolescents by including gender and migration background in the model as sociodemographic predictors. Because previous findings have shown that gender and migration background can act as risk factors that cause different findings and thus might be highly influential on resilience classes, we expected that both predictors could be predictive of class membership (Hypothesis 3; Bustamante et al., 2017; Glied & Pine, 2002).

## Methods

### Participants and procedure

We collected data in a National Centre of Competence in Research On the Move project called Overcoming Inequalities With Education – School and Resilience. The Swiss National Science Foundation funded the study. Participants were 375 adolescents (46.7% females) from the Swiss cantons of Aargau, Basel-City, and Solothurn who completed a questionnaire in class at the beginning of their seventh grade year (International Standard Classification of Education 2; Wave 1) and at the beginning of their eighth grade year (International Standard Classification of Education 3; Wave 2) of lower secondary education school in 2019 and 2020. The relatively long time interval of approximately 1 year allowed for variances in the response patterns. In Wave 1, all adolescents were between the ages of 11 and 15 years with a mean of 12.67 years ($SD = .68$). In Wave 2, 317 adolescents (44.8% females) were still participating in the study, being on average 13.61 years old ($SD = .67$). No students withdrew from the study; all students not participating in Wave 2 had changed classes or schools.

The study was conducted according to the World Medical Association's Declaration of Helsinki (World Medical Association, 2013). Furthermore, the Cantonal Bureaus for Education and the Ethics Committee (for psychological and related research) of the Faculty of Arts and Social Sciences at the University of Zurich endorsed the data collection. The students and their legal guardians gave written consent to participate in the study.

### Measures

### Demographics

Age and gender were assessed as single items. However, migration background was coded with the information on the children's and parents' nationalities and their countries of birth. Migration background was introduced as an official statistical category in 2005 (Horvath, 2019). We defined having a migration background as when either the child or their parent was born outside of Switzerland and/or had more than Swiss nationality. If one of these conditions did not apply, the student was categorized as not having a migration background.

### Hopkins Symptom Checklist–25

The Hopkins Symptom Checklist–25 (HSCL-25; Derogatis et al., 1974) is a 25-item scale derived originally from the 90-item Symptom Checklist (Derogatis, 1994). It is a shorter version of the initial self-report questionnaire, the HSCL (Derogatis et al., 1974), and comparisons to longer versions (e.g. HSCL-56 or HSCL-80) have yielded reliable response consistency (Winokur et al., 1984). The scale includes two subscales – Anxiety (10 items, e.g. 'Feeling fearful') and Depression (15 items, e.g. 'Feeling down or blue') – that can be aggregated for a total psychological distress score. Furthermore, the scale ranges from 1 (*not at all*) to 4 (*extremely*). It shows satisfactory validity and reliability values of $a = .84$ for the Anxiety subscale, $a = .91$ for the Depression subscale, and $a = .94$ for the total scale in the German-speaking version (Petermann & Brähler, 2014). Due to the participants' age range (11–16 years), the item 'Loss of sexual interest' was left out.

### Resilience Scale for Adolescents

The Resilience Scale for Adolescents (Hjemdal et al., 2006) is a 28-item self-report scale that includes five subscales (Personal Competence, Social Competence, Structured Style, Social Resources, and Family Cohesion). It measures protective factors on a five-point-Likert scale ranging from 1 (*totally disagree*) to 5 (*totally agree*). The scale has shown satisfying reliability and validity in different (cross-cultural) studies with Cronbach's alphas from .69 (Structured Style) to .85 (Family Cohesion) for the subscales and $a = .94$ for the total score (e.g. Anyan et al., 2021; Hjemdal et al., 2006; Janousch et al., 2020).

### Statistical analyses

We conducted the statistical analysis for this study in three steps. First, descriptive statistics were presented and differences in the indicators across the two time points were examined using independent *t* tests in IBM SPSS Statistics (Version 24; IBM Corp., 2016). Second, we separately identified resilience patterns across Wave 1 and Wave 2 using consecutive LCAs. Third, we conducted an LTA to determine longitudinally whether the number and size of the latent classes replicated from the cross-sectional LCA and the structure remained the same across both time points (test of measurement invariance; Geiser et al., 2008). Fourth, through a R3STEP approach, we investigated gender and migration background as predictors of class membership in both waves. The R3STEP allows for stable class solutions and parameter estimates that are less biased (Asparouhov & Muthén, 2014).

LCA (Clogg, 1995; McCutcheon, 1987) is a statistical method used to identify divergent subgroups within a certain sample who share outward characteristics (Weller et al., 2020). It is needed to run an LTA. The assumption underlying LCA, as a person-centred approach, is that based on categorical indicator variables, latent groups exist. These groups are referred to as latent classes (or groups) because a group membership cannot be directly observed (Geiser et al., 2014). Rather, they indicate a latent heterogeneity in a certain sample by grouping participants that show similar patterns in the same class (B. O. Muthén & Muthén, 2000). Thus, the patterns between classes can be highly dissimilar (Geiser et al., 2008).

Because the series of items being examined in an LCA are categorical, we dichotomized the data of all indicators (Anxiety, Depression, Personal Competence, Social Competence, Structured Style, Social Resources, and Family Cohesion) into high (1) vs. low (0) groups by using a median split. Instead of using a latent profile analysis requiring continuous variables, LCA allows for direct comparisons to the LTA model when dichotomized items are used in all models (including the LTA model). Otherwise, models based on continuous variables would be compared to a model with dichotomized variables, resulting in methodological bias.

LTA (Collins & Lanza, 2010; Lanza et al., 2012) is an extension of LCA over time. LCA represents stable classes at one time point, whereas participants' number or distribution may change classes in LTA. In our analysis, classes were constrained to have the same structure at both time points (measurement invariance across Wave 1 and Wave 2), but the number of participants in each class could vary.

There are three sets of parameters that are estimated in LTA, which we report in this paper. First, latent status membership probabilities can be estimated for the two time points. These probabilities reflect the proportion of participants expected to belong to each latent class in Wave 1 and Wave 2. Second, transition probabilities represent the likelihood of transitioning from one latent class in Wave 1 to another class in Wave 2. Third, item-response probabilities provide information on the correspondence between the observed indicators and the latent class membership at both time points (Lanza et al., 2010).

LCA, LTA, and the adjusted multinomial regression using the R3STEP-procedure were conducted in Mplus 8.3 (L. K. Muthén & Muthén, 1998) to investigate goodness-of-fit statistics, model parameters, and standard errors. All LCA and LTA models were assessed with several indicators: the Akaike information criterion (AIC; Akaike, 1998), the Bayesian information criterion (BIC; Schwarz, 1978), the sample-size adjusted Bayesian information criterion (aBIC; Schwarz, 1978; Sclove, 1987), the Vuong–Lo–Mendell–Rubin likelihood ratio test (LMR-LRT; Lo, 2001), the Lo–Mendell–Rubin adjusted likelihood ratio test (aLMR-LRT; Lo, 2001), and the bootstrap likelihood ratio test (BLRT; McCutcheon, 1987; McLachlan et al., 2019; McLachlan & Peel, 2000).

## Results

### Descriptives and *t* tests

As shown in Table 1, after running a *t* test on the seven indicators, we identified only minor or no significant study-wave effects. On one hand, the mean values increased for the subscale Depression between Wave 1 and Wave 2 with a small effect size. On the other hand, small effects could be detected in changes in Social Resources, Family Cohesion and the total score of the Resilience Scale for Adolescents. The mean values in these protective factors decreased from 2019 to 2020.

We then dichotomized the indicators to conduct the LCA and LTA. Table 2 shows the distribution of indicator and outcome variables after recoding.

### *Latent class analyses*

As a second step, we identified participants' resilience patterns by conducting separate LCA analyses for both time points, using the same seven indicators. A series of latent class models was estimated, and the number of classes ranged from one to four in both analyses. Table 3 displays the goodness-of-fit indices for each model at both time points.

For Wave 1, the lowest BIC; the highest entropy; good classification accuracy; and significant LMR-LRT, aLMR-LRT, and BLRT could be detected in the three-class solution. The four-class solution yielded nonsignificant LMR-LRT and aLMR-LRT even though it showed better AIC and aBIC values. However, the difference between the information criteria values of the three- and four-class solutions was small. Therefore, a three-class solution was chosen as the best-fitting model for Wave 1 (see, Figure 1).

**Table 1.** Wave 1 (n = 375) and wave 2 (n = 317) reliabilities (Cohen's Alpha and McDonald's Omega), sample means, standard deviations, effect sizes of all indicators.

| Variable | Range | Wave 1 α 95% CI [LL, UL] | Wave 1 ω 95% CI [LL, UL] | Wave 2 α 95% CI [LL, UL] | Wave 2 ω 95% CI [LL, UL] | Wave 1 M (SD) | Wave 2 M (SD) | Cohen's d/Pearson product–moment correlation coefficient r |
|---|---|---|---|---|---|---|---|---|
| Anxiety | 1–4 | .86 [.82, .88] | .86 [.82, .88] | .87 [.84, .89] | .87 [.85, .89] | 1.95 (.62) | 1.96 (.64) | |
| Depression | 1–4 | .93 [.91, .94] | .93 [.91, .94] | .94 [.93, .95] | .94 [.93, .95] | 1.79 (.67)** | 1.87 (.75)** | −.17/ −.08 |
| Personal competence | 1–5 | .70 [.63, .75] | .70 [.61, .75] | .78 [.72, .81] | .78 [.72, .82] | 3.89 (.58) | 3.82 (.64) | |
| Social competence | 1–5 | .70 [.62, .75] | .70 [.62, .75] | .77 [.70, .82] | .77 [.71, .82] | 4.03 (.65) | 3.95 (.71) | |
| Structured style | 1–5 | .58 [.50, .65] | .58 [.49, .66] | .59 [.49, .67] | .59 [.47, .67] | 3.66 (.72) | 3.65 (.67) | |
| Social resources | 1–5 | .79 [.74, .83] | .79 [.73, .84] | .86 [.80, .89] | .86 [.79, .90] | 4.49 (.58)** | 4.42 (.69)** | .15/.08 |
| Family cohesion | 1–5 | .86 [.82, .89] | .86 [.82, .89] | .90 [.87, .93] | .90 [.87, .92] | 4.33 (.68)* | 4.23 (.75)* | .15/.07 |
| HSCL total | 1–4 | .94 [.93, .95] | .94 [.93, .95] | .95 [.94, .96] | .95 [.94, .96] | 1.86 (.61) | 1.91 (.66) | |
| READ total | 1–5 | .90 [.88, .92] | .90 [.87, .91] | .92 [.90, .94] | .92 [.89, .94] | 4.10 (.49)* | 4.01 (.55)* | .14 /.07 |

HSCL = Hopkins Symptom Checklist; READ = Resilience Scale for Adolescents.
* $p$ < .05. ** $p$ < .01. These values were calculated between Wave 1 and Wave 2. Cohen's $d$ was only reported when results were significant.

**Table 2.** Wave 1 (n = 375) and wave 2 (n = 317) distribution of dichotomized variables.

| | Low (0) | | High (1) | |
|---|---|---|---|---|
| Variable | n | % | n | % |
| Anxiety t1 | 182 | 51.1 | 174 | 48.9 |
| Anxiety t2 | 129 | 41.3 | 183 | 58.7 |
| Depression t1 | 183 | 51.0 | 176 | 49.0 |
| Depression t2 | 126 | 40.4 | 186 | 59.6 |
| Personal competence t1 | 176 | 49.3 | 181 | 50.7 |
| Personal competence t2 | 139 | 44.3 | 175 | 55.7 |
| Social competence t1 | 176 | 49.0 | 183 | 51.0 |
| Social competence t2 | 169 | 54.0 | 144 | 46.0 |
| Structured style t1 | 208 | 57.9 | 151 | 42.1 |
| Structured style t2 | 145 | 46.3 | 168 | 53.7 |
| Social resources t1 | 189 | 52.4 | 172 | 47.6 |
| Social resources t2 | 133 | 42.2 | 182 | 57.8 |
| Family cohesion t1 | 193 | 53.8 | 166 | 46.2 |
| Family cohesion t2 | 123 | 42.6 | 166 | 57.4 |
| HSCL total t1 | 165 | 48.0 | 179 | 52.0 |
| HSCL total t2 | 122 | 40.8 | 177 | 59.2 |
| READ total t1 | 171 | 47.8 | 187 | 52.2 |
| READ total t2 | 130 | 41.3 | 185 | 58.7 |
| | Female | | Male | |
| | n | % | n | % |
| Gender | 175 | 46.7 | 200 | 53.3 |
| | Native | | Migrant | |
| | n | % | n | % |
| Migration background | 89 | 24.6 | 273 | 75.4 |

HSCL = Hopkins Symptom Checklist; READ = Resilience Scale for Adolescents.

**Table 3.** Model fit indices for latent class analyses of protective factors and mental health issues for both time points.

| Wave | Number of classes | AIC | BIC | ABIC | Entropy | LMR-LRT p values | ALMR-LRT p value | Sample proportion per class | Classification accuracy | BLRT p value |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 3,481.154 | 3,508.415 | 3,486.207 | | | | 363 | | |
| | 2 | 3,191.940 | 3,250.357 | 3,202.768 | .716 | <.001 | < .001 | (197; 54%), (166; 46%) | .913–.920 | < .001 |
| | **3** | **3,149.315** | **3,238.886** | **3,165.917** | **.794** | **< .001** | **< .001** | **(158; 44%), (132; 36%), (73; 20%)** | **.873–.941** | **< .001** |
| | 4 | 3,129.972 | 3,250.699 | 3,152.350 | .725 | .12 | .12 | (53; 15%), (149; 44%), (98; 29%), (42; 12%) | .790–.904 | < .001 |
| 2 | 1 | 2,976.580 | 3,002.892 | 2,980.690 | | | | 317 | | |
| | 2 | 2,720.181 | 2,776.564 | 2,728.988 | .717 | <.001 | < .001 | (175; 55% (142; 45%) | .907–.925 | < .001 |
| | **3** | **2,679.566** | **2,766.021** | **2,693.070** | **.789** | **< .05** | **< .05** | **(82; 26%), (114; 36%), (121; 38%)** | **.870–.961** | **< .001** |
| | 4 | 2,661.974 | 2,778.500 | 2,680.175 | .733 | .08 | .08 | (77; 24%), (72; 23%), (104; 33%), (64, 20%) | .803–.887 | < .001 |

Chosen number of classes are in bold. AIC = Akaike information criterion; BIC = Bayesian information criterion; ABIC = sample-size adjusted Bayesian information criterion; LMR-LRT = Vuong–Lo–Mendell–Rubin likelihood ratio test; ALMR-LRT = Lo–Mendell–Rubin adjusted likelihood ratio test; BLRT = bootstrap likelihood ratio test.
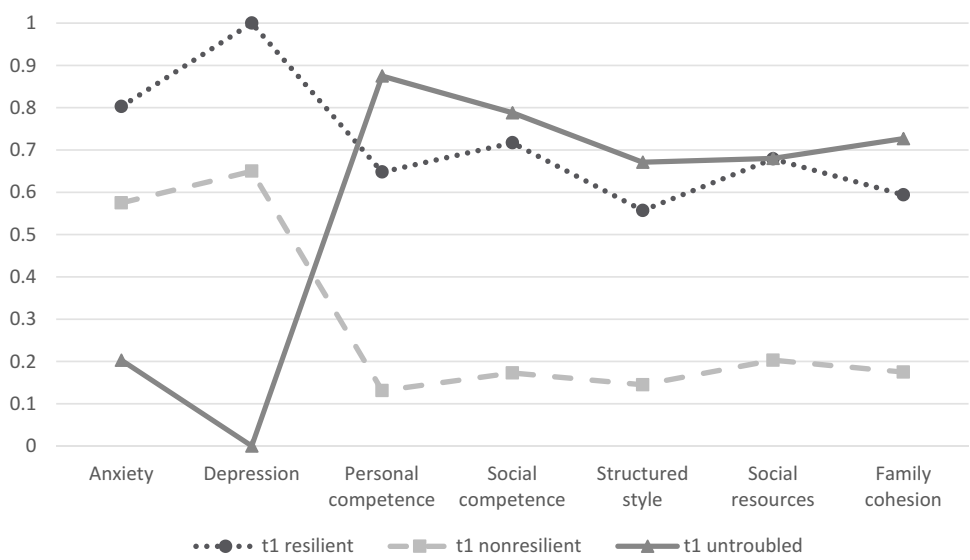
**Figure 1.** Profile plot for Wave 1 latent class analysis with class-specific probabilities of the indicators' respective high levels.
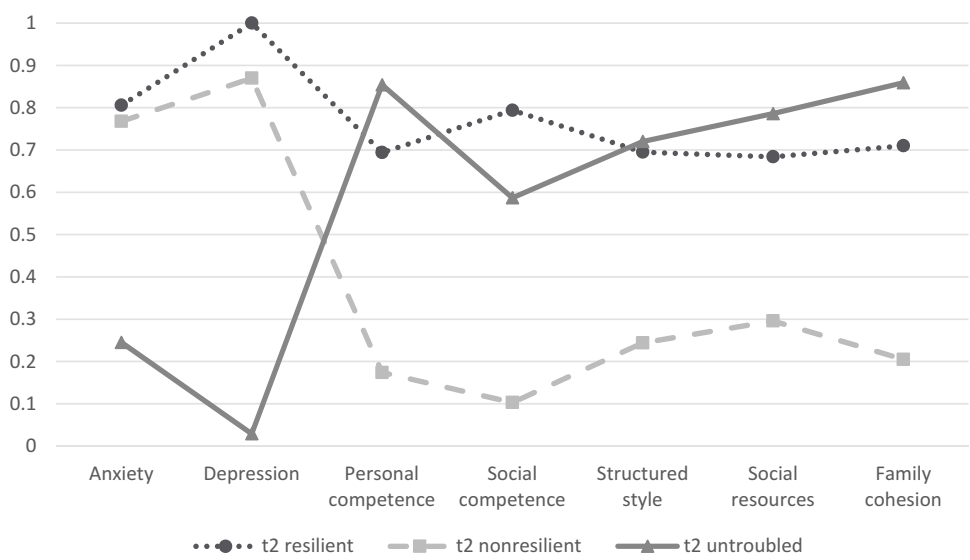


**Figure 2.** Profile plot for Wave 2 latent class analysis with class-specific probabilities of the indicators' respective high levels.

For Wave 2, we found similar results in all models. Just as in the Wave 1 analysis, the lowest BIC; highest entropy value; good classification accuracy; and significant LMR-LRT, aLMR-LRT, and BLRT supported a three-class solution. Similar to Wave 1, the AIC and aBIC values were lower in the four-class solution. However, once again, the LMR-LRT and aLMR-LRT indicated that the four-class solution did not fit the data better compared to the three-class solution. Thus, we chose a three-class solution for the Wave 2 analysis, too (see, Figure 2).

When comparing the distribution of the seven indicators in the three identified classes for Wave 1 ($n = 363$) and Wave 2 ($n = 317$), we identified some similarities and differences. As shown in Figure 1, the first class with high mental health issues and high protective factor levels at both time points could be considered the resilient group (Wave 1 = 21.0%; Wave 2 = 26.3%). The second group had high levels of mental health issues but very low protective factors. This group was the so-called nonresilient group (Wave 1 = 42.8%; Wave 2 = 37.3%). Finally, one group showed low levels of mental health issues and very high levels of protective factors, the so-called untroubled class (Wave 1 = 36.2%; Wave 2 = 36.4%).

## Latent transition analysis

To test the hypothesis about stability and changes in resilience patterns, we ran a series of LTA nested models including Wave 1 and Wave 2 indicators. Table 4 presents the model fit information used and shows that the optimal number of classes resulted in three classes, similar to the individual LCA analyses. The AIC and aBIC resulted in the lowest values, and the entropy value was the highest for a three-class solution across all nested models. Furthermore, the sample proportion per class was also satisfying. Thus, in order to apply the rule of deference (i.e. to choose the most parsimonious model) to more constrained and parsimonious models, we chose the three-class solution for the longitudinal comparison.

**Table 4.** Model fit indices for latent transition analyses of protective factors and mental health issues for wave 1 and wave 2 nested models.

| Number of classes | AIC | BIC | ABIC | Entropy | Sample proportion per class |
|---|---|---|---|---|---|
| 2 | 5,880.714 | 5,947.427 | 5,893.490 | .698 | C1: (189; 51%), (185; 49%); C2: (201; 54%), (173; 46%) |
| **3** | **5,730.946** | **5,844.749** | **5,752.741** | **.745** | **C1: (146; 39%), (76; 20%), (152; 41%) C2: (127; 34%), (113; 30%), (134; 36%)** |
| 4 | 5,645.951 | 5,814.694 | 5,678.267 | .737 | C1: (101; 27%), (73; 20%), (79; 21%), (121; 32%) C2: (61; 16%), (86; 23%), (115; 31%), (112; 30%) |

Chosen number of classes are in bold. AIC = Akaike information criterion; BIC = Bayesian information criterion; ABIC = sample-size adjusted Bayesian information criterion; LMR-LRT = Vuong–Lo–Mendell–Rubin likelihood ratio test; ALMR-LRT = Lo–Mendell–Rubin Adjusted likelihood ratio test; BLRT = bootstrap likelihood ratio test; C1 = Class 1; C2 = Class 2.

**Table 5.** Item–response probabilities.

| Probability of response to indicators | Untroubled | Resilient | Nonresilient |
|---|---|---|---|
| Anxiety | | | |
| Low | .812 | .161 | .347 |
| High | .188 | .839 | .653 |
| Depression | | | |
| Low | .962 | .083 | .244 |
| High | .038 | .917 | .756 |
| Personal competence | | | |
| Low | .145 | .359 | .854 |
| High | .855 | .641 | .146 |
| Social competence | | | |
| Low | .306 | .255 | .892 |
| High | .694 | .745 | .108 |
| Structured style | | | |
| Low | .319 | .375 | .827 |
| High | .681 | .625 | .173 |
| Social resources | | | |
| Low | .280 | .338 | .764 |
| High | .720 | .662 | .236 |
| Family cohesion | | | |
| Low | .244 | .358 | .807 |
| High | .756 | .642 | .193 |

Item–response probabilities constrained to be equal at Wave 1 and Wave 2.

The item-response probabilities for each latent class (Table 5) indicated the participants' resilience patterns and gave a sense of what characterized these three classes. The first latent class was labelled, just as in the individual LCAs, untroubled because of (very) high probabilities of participants reporting low values for mental health issues but high values for protective factors. Interestingly, there was substantial homogeneity among individuals in the untroubled class, with almost all students reporting low values for depressive symptoms. The second class, labelled resilient, was also characterized by high probabilities of reporting a high value for protective factors, but contrary to the untroubled class, this class also had high probabilities of reporting high values for anxiety and depression. Once again, strong homogeneity was detected among individuals in this class for the indicator depression. At the same time, the response patterns (i.e. different levels of protective factors) differed much more for protective factors in the resilient class compared to the untroubled class. The last class, the so-called nonresilient group, showed similar results for the mental health issue indicators but with a greater heterogeneity in their response patterns. Although the individuals in the resilient group were much more likely to show high protective factors, the nonresilient students were more likely to report low values in this area.

When investigating the distribution of the three classes more closely in the nested LTA model, we detected significant changes (Table 6). First, the resilient class was a highly stable class, with over 90% of all participants being represented in the same class in Wave 1 and Wave 2. Interestingly, barely any students moved from this group to the untroubled, and only a small number changed to the nonresilient class. Second, the untroubled and the nonresilient classes showed similar levels of stability. However, the transition probabilities varied for these two classes. On one hand, the numbers of participants moving from the nonresilient group to the other two groups were almost equal (14% and 15%). On the other hand, a significant number of students moved from the untroubled group to the resilient group in Wave 2 (22%). Less than 10% of the participants transitioned from the untroubled group to the nonresilient group. These transitions can also be seen in the final class counts and proportions for each latent class variable in Table 7. Furthermore, Table 7 also shows the distribution of the two sociodemographic variables, gender, and migration background, within each class at both time points. The untroubled and nonresilient classes each decreased about 5%, whereas the resilient class increased about 10%.

Table 6. Latent transition probabilities based on the estimated model.

| Classes | Untroubled | Resilient | Nonresilient |
|---|---|---|---|
| Untroubled | **.69** | .22 | .09 |
| Resilient | .03 | **.91** | .07 |
| Nonresilient | .15 | .14 | **.71** |

Transition probabilities in bold correspond to membership in the same latent status at both times. Rows are for Wave 1, columns are for Wave 2.

Table 7. Final class counts and proportions for each latent class variable based on their most likely latent class pattern and distribution of sociodemographic variables within each class for both waves.

| | | | | Gender | | | | Migration background | | | |
| | | | | Female | | Male | | Native | | Migrant | |
| | Class | Class count | Class proportions | n | % | n | % | n | % | n | % |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Wave 1 | Untroubled | 146 | 39.0% | 62 | 42.5 | 84 | 57.5 | 35 | 24.3 | 109 | 75.7 |
| | Resilient | 76 | 20.3% | 41 | 53.9 | 35 | 46.1 | 17 | 24.3 | 53 | 75.7 |
| | Nonresilient | 152 | 40.6% | 71 | 46.7 | 81 | 53.3 | 37 | 25.0 | 111 | 75.0 |
| Wave 2 | Untroubled | 127 | 34.0% | 46 | 36.2 | 81 | 63.8 | 31 | 24.8 | 94 | 75.2 |
| | Resilient | 113 | 30.2% | 60 | 53.1 | 53 | 46.9 | 27 | 25.2 | 80 | 74.8 |
| | Nonresilient | 134 | 35.8% | 68 | 50.7 | 66 | 49.3 | 31 | 23.8 | 99 | 76.2 |

**Table 8.** Multinomial logistic regression of the covariates gender and migration background to the identified latent status membership for both waves (R3STEP).

| Wave | Predictor | Resilient vs. untroubled | | Resilient vs. nonresilient | | Untroubled vs. nonresilient | |
|---|---|---|---|---|---|---|---|
| | | Estimate (SE) | OR | Estimate (SE) | OR | Estimate (SE) | OR |
| 1 | Gender [a] | −0.44 (0.33) | 1.546 | −0.52 (0.37) | 1.677 | −0.08 (0.28) | 0.922 |
| | Migration background [b] | 0.10 (0.38) | 0.906 | 0.12 (0.42) | 1.128 | −0.22 (0.32) | 0.803 |
| 2 | Gender [a] | −1.02** (0.35) | 0.36 | −0.36 (0.38) | 0.70 | 0.66* (0.31) | 1.94 |
| | Migration background [b] | 0.250 (0.39) | 1.28 | 0.22 (0.43) | 1.25 | −0.03 (0.34) | 0.97 |

Estimate = β from R3STEP analysis; OR = odds ratio.
[a]1 = male, 2 = female; [b] 0 = migrant, 1 = native.
* p < .05. ** p < .01.

### Covariates (R3STEP)

To determine whether gender and migration background were predictive of resilience pattern membership in Wave 1 or Wave 2, we conducted a multinomial logistic regression (Table 8). Interestingly, neither gender nor migration background were significant predictors of latent class membership in Wave 1.

However, gender was a strong predictor in Wave 2 (showing higher effectiveness) for two pairwise comparisons. Boys were more likely to be part of the untroubled class in comparison to the resilient and nonresilient classes. Therefore, girls were more likely to be in the resilient or nonresilient classes compared to the untroubled class. No pairwise comparison was significant for the predictor migration background in Wave 2.

### Discussion

Early adolescence is the beginning of the pubertal transition that encompasses biological, psychological, physical, and social changes (Steinberg, 2020). Thus, this period of time is characterized by possible fluctuations in resilience. Furthermore, the COVID-19 pandemic might be a challenge to adolescents' mental health, and not much is known yet about its possible impacts on students' resilience. Therefore, this study aimed to gain a greater understanding of Swiss early adolescents' resilience patterns by conducting a longitudinal, person-centred study using LCA (at two separate time points – August/September 2019 and 2020) and LTA (at the same time points) approaches. The LCAs and LTA were conducted using the following indicators: anxiety, depression, Personal Competence, Social Competence, Structured Style, Social Resources, and Family Cohesion.

The findings revealed three heterogeneous groups (i.e. resilient, nonresilient, and untroubled) with unique stability and transition patterns exhibited across time. Furthermore, a multinomial regression with the variables gender and migration background was conducted on the LTA groups, demonstrating that only gender was a significant predictor in Wave 2. Boys were more likely to be part of the untroubled group than the resilient or nonresilient ones in Wave 2; thus, girls were more likely to be part of the resilient or nonresilient classes than the untroubled one.

The study demonstrated several strengths. The first strength was investigating resilience with mental health disorders and protective factors that are highly dependent on each other in a person-centred approach and are at the centre of resilience theory. Second, we examined these indicators across 1 year. Because adolescence is a time of possibly fluctuating mental health and resilience factors, collecting data longitudinally was valuable. Third, our investigation provides new

information about the association between protective factors, mental health disorders, and demographic characteristics in the context of the COVID-19 pandemic. The impact of the pandemic on mental health has still not been sufficiently explored.

### Resilience classes and patterns in times of COVID-19

Previous person-centred research supported a three- or four-group solution, typically with flourishing, vulnerable, troubled, and symptomatic but content groups (Moore et al., 2019; Xiong et al., 2017; J. Zhou et al., 2020). These analyses were conducted with a focus on a dual-factor model of mental health, where well-being and psychopathological aspects were used as indicators. However, in this study, even though we confirmed a three-class solution (J. Zhou et al., 2020), the indicators were psychopathological factors such as anxiety and depression but not well-being factors. Instead, protective factors that focused on a resilience concept were included. Therefore, we investigated resilience rather than a dual-factor model of mental health.

These findings need to be discussed by considering the timing of the data collection in August/September 2019 and August/September 2020, which was during the recent pandemic. As mentioned, Switzerland has been massively affected by the COVID-19 crisis (Salathé et al., 2020). During the country's first ever lockdown (Nivette et al., 2021) and ensuing slowdown, students had to be taught at home, families had to spend much more time together, and everyone had to adapt to an uncertain situation. The second data collection (August/September 2020, first quarter of the school year) fell right into a time of the pandemic when the first wave was over, but Switzerland was about to face the second wave (November 2020, second quarter of the school year). Because it has not been a regular school year, it was not surprising to find distinctive differences among psychopathological and protective factors in our analyses. Hence, in additional to the time of pubertal transition, mental health and protective factors might have been highly influenced by COVID-19 containment measures and the uncertainties that came along with the pandemic. This situation might have had diverse impact on the socioemotional development of children and adolescents related mostly to their sources of support at home (e.g. family, security), socioeconomic status (e.g. access to infrastructure for home education), and especially a deterioration in their social relations (peers, teachers, the community). Specifically for the nonresilient students, who were already at risk in Wave 1, the situation drastically worsened in terms of mental health issues and the protective factor of Social Competence. Contrary to the findings in Chinese adolescents, where anxiety and depression levels increased during the pandemic, other studies (e.g. Barendse et al., 2021; Mohler-Kuo et al., 2021) have supported the findings of this study. Depression symptoms increased significantly, whereas anxiety levels remained stable overall. The authors made the assumption that depression levels may have been influenced by less social stimulation and high levels of uncertainty followed by low possibilities to influence one's own situation. Furthermore, anxiety is multifaceted and, therefore, some types of anxiety might increase whereas other types decrease during a pandemic. For example, social anxiety might have temporarily declined because of fewer opportunities for social interactions, whereas OCD and health or general anxieties might have increased because of the global pandemic and the uncertainties that came along with it.

However, the changes in protective factors might also have been influenced by the pandemic and the transitional stage of puberty. Social competences subsided for the nonresilient and untroubled groups, whereas the resilient class reported even higher levels. The time during lockdown and slowdown when schools were closed and social gatherings (sports clubs, leisure centres, etc.) were not allowed had greater effects on the group already at risk. Nevertheless, Social Resources and Family Cohesion increased in all three groups. Peer relationships are of paramount importance during puberty for receiving feedback, being sensitive to status, and feeling socially connected (Kilford et al., 2016; Schriber & Guyer, 2016). Therefore, social media might have offered invaluable opportunities for staying connected during the pandemic. Video calls that more closely resemble in-person interactions than just passively consuming memes and videos on social media platforms

might have especially added to the formation of stronger social connections (Hamilton et al., 2020). Additionally, the time during lockdown was an opportunity for some families to spend more time together than before or since. That might have positively influenced the protective factor of Family Cohesion. However, what is apparent is that the increase in Family Cohesion is lower for nonresilient students than for the other two groups. It is possible that the family environment might have become a stressor in this context. Furthermore, it would be interesting to find out more about family relations and backgrounds in all groups because the COVID-19 pandemic has also put financial strains on and elevated mental health disorders in parents. This might have influenced the protective factor Family Cohesion as well.

Personal Competences that focus on aspects such as goal-orientation and self-perception changed only slightly for the resilient and nonresilient classes. This factor increased slightly, whereas Structured Style improved in all groups. This might have been caused by changing to a distance-learning setting at schools not only during lockdown but also during slowdown. Even though it lasted for only 2 months at most schools, remote teaching led to much more learner agency, responsibilities, flexibilities, and choices that required careful planning and improved self-organization (Bozkurt & Sharma, 2020). That might have been a challenge for all students, but those showing high levels of mental health issues especially improved in Structured Style. They might have had to adapt more on an individual level to be able to cope with the situation. Another explanation could be that the challenging circumstances of the COVID-19 pandemic activated certain resources directly related to the situation, because a moderate amount of exposure to adversity creates opportunities to develop and foster protective factors (Dienstbier, 1992; Höltge et al., 2018).

By conducting an LTA, a measurement invariance for the separate LCAs, we observed transition patterns. They revealed a predominant tendency towards stability rather than change among Swiss pupils. These results are quite consistent with previous studies showing that the flourishing group, which is comparable to the untroubled group in our study, exhibited high stability across the year (Moore et al., 2019; J. Zhou et al., 2020). However, the most stable group was the resilient group, with 90% stability. This indicates that even though they were showing high levels of mental health issues before the COVID-19 pandemic, they were still able to cope with the additional stress related to the forced changes in their lives and the uncertainty about their future. In this group, protective factors of resilience were already active due to previous stressors; thus, adolescents could benefit from this active protection. The nonresilient and untroubled groups had lower but still important stability levels of about 70%, which is line with previous studies (Moore et al., 2019; J. Zhou et al., 2020). In contrast to previous studies where adolescents were more likely to show a 'recovery' pattern (Kelly et al., 2012; Moore et al., 2019; Xiong et al., 2017), a great number of students moved from showing only low levels of mental health issues in the untroubled class towards the resilient group with similar levels of protective factors but much higher mental disorder levels. In this group, the ones who transitioned from not having high levels of emotional mental health issues (anxiety and depression), it is possible to see the greatest impact of the global pandemic on youths' mental well-being.

Resilience protects against the detrimental effect of stressors and the development of mental health issues, but it is not a panacea for all physical or mental ills. Certainly, we can speculate that adolescents who now exhibit more mental health issues, but higher levels of active protective factors might pass through this period of their lives with effective resources for better adaptation than those whose protective factors remained lower in the second wave (nonresilient). Moreover, the highest number of participants was part of the resilient class in Wave 2. However, more students moved from the nonresilient group towards the resilient and untroubled classes, and the nonresilient and untroubled groups decreased about 5% each in Wave 2, which partially supports the previous findings. This is highly relevant when considering the context of the pandemic: Most students had high levels of protective factors and adapted relatively well despite the demanding circumstances.

These findings also support Masten's (2014) idea of ordinary magic, which states that resilience arises from common processes and, thus, it is not rare for people to overcome adversities and show resilience.

Finally, we examined the influence of gender and migration background. The study supported previous findings that gender can be a predictor of resilience patterns (e.g. Glied & Pine, 2002), but in contrast to other previous research, neither gender in Wave 1 nor migration background in both time points were predictive of resilience patterns. In Wave 2, boys were more likely to be part of the untroubled class than the nonresilient and resilient groups. This means girls tend to a larger extent to be part of the extreme groups than boys, having either high or low levels of protective factors combined with high levels of mental health issues. This is in line with other studies showing higher rates of depression and anxiety for girls than for boys (e.g. Mohler-Kuo et al., 2021; Nearchou et al., 2020; Panda et al., 2021). A Chinese study investigating 493 junior high school students and 532 high school students demonstrated that during the COVID-19 pandemic, higher resilience was significantly associated with male gender in both samples (Zhang et al., 2020). These results are consistent with previous findings in different samples before the COVID-19 pandemic (e.g. Campbell-Sills et al., 2009; Erdogan et al., 2015).

As shown in Table 7, the distribution of adolescents with and without a migration background is very similar across all three classes for both waves. Thus, it is not surprising that this variable did not act as a significant predictor even though previous findings, such as a review investigating the health of Swiss migrant children and adolescents (Jaeger et al., 2012), have proven otherwise. Similarly, most European studies report a higher prevalence of mental health issues in adolescents with a migration background (e.g. Dimitrova et al., 2016). However, there is also the so-called 'immigrant paradox' where immigrant adolescents show higher mental health than their native peers (e.g. Mood et al., 2016). This might be explained through the 'resilience perspective', postulating that adolescents with a migration background are doing well because of their access to resources that protect or promote their well-being and mental health (Motti-Stefanidi & Masten, 2017). Furthermore, dichotomizing the variable in a rather strict and conservative manner resulted in an extremely high number of students with a migration background. We might have found different results if we had distinguished between the different generations (at least between the first- and second-generation immigrants). According to recent literature and research, what might be much more important is not the adolescents' nationalities and migration background status. Rather socio-demographic background variables play an important role when investigating (Swiss) migrant and non-migrant adolescents (Hüsler & Werlen, 2010) and might act as a moderator between migration status and adolescents' mental health (Delaruelle et al., 2021). Therefore, we conclude that these findings should be treated with caution. Future investigations should analyse migration background by using different categorization systems, considering the different generations but also by paying close attention to socio-demographic background variables such as social capital.

There is one crucial practical implication of understanding the resilience patterns of Swiss adolescents. Group-specific health promotion and intervention programmes might help adolescents more directly and specifically. Maybe nonresilient and resilient groups need help mitigating depression and anxiety levels, whereas the nonresilient group needs additional support in enhancing their protective factors. Displaying high anxiety and/or depressive symptoms might occur in conjunction with poor peer relationships or poorer health in general, which might negatively influence school-related aspects such as grades and/or behaviour (De Matos et al., 2003) and the future development and mental well-being of the adolescents in these groups. Therefore, health promotion and intervention programmes should be embedded in schools where school professionals and parents can be included to help pupils improve their situations by decreasing mental health issues and increasing protective factors.

All findings highlight the importance of group-specific research, which may call for intervention programmes based on person-centred findings. Instead of following a one-size-fits-all approach, we need to evaluate early adolescents more individually to identify subgroups and potentially develop

tailored programmes and solutions that might help those in the relevant groups. In addition, more research is needed to obtain a clearer picture of resilience patterns by including more and/or different risk and protective factors, as well as symptoms in the model.

### *Limitations*

Beyond this study's strengths, certain limitations and their resulting implications for future research need to be considered. First, to give a more precise picture of adolescents' resilience trajectories, a certain risk factor should have been included. However, the pupils only answered questions about their mental health and protective factors. Therefore, it would be crucial for future research to have a certain stressor included in the study.

Second, albeit the study has collected data across 1 year, a longitudinal design of three or more waves would provide a clearer picture of casualties. Thus, future research should include at least one more data collection to provide more insight into these patterns.

Third, dichotomizing data always restricts the findings. By applying a median split, participants are unnaturally divided into two groups. However, it is very likely that some students have scored just slightly above or below the median. That could cause serious bias in the analyses and should be interpreted with caution. However, it is a well-known issue (Iacobucci et al., 2015; Rucker et al., 2015) and a necessary step in conducting an LCA and LTA.

Fourth, all data were gathered from one source, the students. The data are based on self-reports, which could additionally cause a bias in the analyses. Survey studies with adolescents benefit from including multiple sources, such as parents and teachers. This might reduce the effect of method bias or bias the social expectancy causes, which might interfere with the reliability of the self-report measurement (e.g. Parker, 1966).

Finally, this study cannot completely prove whether all findings are related to the COVID-19 pandemic. The discussed findings are based on those of other studies and assumptions that might explain the results. Nevertheless, the study was not a COVID-19-related study closely investigating resilience patterns during the pandemic by using COVID-19-specific items. Future investigations that have a stronger focus on pandemic-related questions might be able to put additional findings into perspective.

Further recommendations for future research are to use more variables in general in the model, for example, other mental health and protective factors. In addition, the findings should be replicated in different samples such as adults, and it should be investigated at a later point in time during the pandemic.

## Acknowledgements

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Funding

## Notes on contributors

*Clarissa Janousch* is currently a doctoral student at the University of Zurich, working in the resilience project Overcoming Inequalities with Education—School and Resilience at the University of Applied Sciences and Arts Northwestern Switzerland. Her thesis focuses on the context-specific nature of resilience by using variable- and person-centered approaches. Before working as a researcher, she was a secondary education teacher.

*Dr. Frederick Anyan* cofounded the Resilience Research Centre at the Department of Psychology, NTNU, where he currently works as a researcher. His research focuses on the competence of at-risk and vulnerable populations, stress and resilience processes in development, loneliness and mental health, and using complex quantitative methodology.

*Dr. Roxanna Morote* is a researcher affiliated to and a cofounder of the Resilience Research Centre at the Department of Psychology, NTNU, where she is currently working as a researcher. Her research interests revolve around the capacity of children, adolescents, and excluded groups of society to create diverse forms of positive adaptation, as well as personal and collective resilience.

*Prof. Dr. Odin Hjemdal* is a clinical psychologist at the Department of Psychology, NTNU and cofounder of the Resilience Research Centre. His research interests include resilience, psychometrics, anxiety, depression, clinical treatment trials using Metacognitive Therapy and Cognitive Behavioral Therapy, as well as developmental psychopathology.

## ORCID

Clarissa Janousch http://orcid.org/0000-0002-4160-9758
Frederick Anyan http://orcid.org/0000-0002-0339-3263
Roxanna Morote http://orcid.org/0000-0003-3607-8574
Odin Hjemdal http://orcid.org/0000-0002-6430-2345

## Ethics approval

First, the Cantonal Bureau for Education in the Cantons of Aargau, Basel-Stadt, and Solothurn approved of the study. Second, the Ethics Committee of the Faculty of Arts and Social Sciences of the University of Zurich proved and endorsed the study. Finally, written informed consent was obtained from participating students as well as from participants' legal guardians or next of kin.

## Data availability

The project leader will make available the data sets presented in this article after 2023 when the project will be completed. Requests to access the data sets should be directed to Wassilis Kassis (wassilis.kassis@fhnw.ch).

## Author's contribution

CJ participated in the study design, collected data, performed statistical analyses and interpretation, coordinated and drafted the first manuscript, and revised the manuscript. FA guided statistical analyses and helped to interpret the data and draft the manuscript. RM and OH contributed to the manuscript revision. All authors read and approved the final manuscript.

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