ORIGINAL PAPER

Adolescents' Covitality Patterns: Relations with Student Demographic Characteristics and Proximal Academic and Mental Health Outcomes

Stephanie A. Moore[1] · Delwin Carter[2] · Eui Kyung Kim[1] · Michael J. Furlong[2] · Karen Nylund-Gibson[2] · Erin Dowdy[2]

Abstract

Identifying and promoting students' social-emotional strengths is essential in building their mental health. Covitality, representing the co-occurrence of psychological strengths, is a helpful framework for characterizing students' well-being. This study used latent profile analysis to identify adolescents' ($n = 11,217$; 50.3% female, 37.8% male; grades 9 [33.7%], 10 [21.0%], 11 [28.9%], and 12 [16.5%]) covitality patterns across 12 social-emotional health domains. We investigated whether student demographic characteristics (i.e., sex, parent educational attainment, ethnic identification) were related to profile membership. We further examined profiles' relations to students' proximal academic and mental health outcomes, including self-reported grades, school connectedness, life satisfaction, and psychological distress. Four covitality profiles were identified—*High, Moderate-High, Moderate-Low,* and *Low*. Profile membership was statistically significantly related to students' sex and socioeconomic circumstances but with small effect sizes. We identified consistent differences across covitality profiles on student self-reported proximal outcomes. Overall, students in profiles with higher covitality levels (*High* and *Moderate-High*) reported (a) higher grades, school connectedness, and life satisfaction and (b) less psychological distress, with students in the *High* profile reporting the most favorable outcomes. Assessing students' strengths and providing interventions focused on building strengths across domains are recommended.

Keywords Adolescents · Covitality · Distress · Latent profile analysis (LPA) · Life satisfaction

Introduction

Mental health is increasingly recognized as more than the absence of a mental disorder (e.g., World Health Organization, 2016). Empirical evidence supporting a dual-factor model of mental health (e.g., Grych et al., 2020; Suldo et al., 2016) asserts that psychological distress and well-being each contribute to mental health. The re-emergence of positive psychology has also contributed to an increased focus on integrating wellness promotion into school-based assessment and intervention (e.g., Nickerson & Fishman, 2013), enabling a comprehensive understanding of pathways to

students' optimal mental health (e.g., Furlong et al., 2014). Research in positive psychology has called for developing and cultivating psychological strengths, resources, and assets among adolescents as a preventive mental health approach (Seligman & Csikszentmihalyi, 2000).

Adolescence is a crucial developmental period characterized by substantive developmental transitions (Petersen et al., 1991) and inclusive of high levels of stress, poor academic performance, and social maladjustment, which in turn are associated with psychopathology in adulthood (Cicchetti & Cohen, 2006; Grant et al., 2006). A conceptual and measurement model capturing psychological strengths in children and adolescents argues that youth psychosocial assets are associated with a higher-order trait, *covitality*, that represents the "synergistic effect of positive mental health resulting from the interplay among multiple positive psychological building blocks" (Furlong et al., 2014a, b, p. 1011). This conceptualization was developed as a counterpart to comorbidity, implicating the co-occurrence of multiple disorders with worse outcomes. Similarly, the covitality

✉ Stephanie A. Moore
  stephanie.moore@ucr.edu

1 School of Education, University of California Riverside, 900 University Ave, 1207 Sproul Hall, Riverside, CA 92521, USA

2 University of California Santa Barbara, Santa Barbara, CA, USA

principle proposes that the combination of psychological strengths is protective against mental health problems and matters more than any individual strength for youths' quality of life.

Researchers of youth well-being have emphasized the need to understand the core components of positive psychosocial development and how they may co-occur and have synergic effects on students' positive school and life outcomes (Lenzi et al., 2015a, 2015b). In line with this effort, Furlong et al. (2014a, 2014b) proposed that mental health comprises 12 positive psychological strengths—derived from the social-emotional learning and positive youth development literatures—that have synergic positive effects on youths' school and life outcomes. These 12 strengths are associated with four second-order social-emotional constructs—(a) *belief-in-self* (self-awareness, self-efficacy, persistence); (b) *belief-in-others* (family coherence, peer support, school support); (c) *emotional competence* (emotion regulation, self-control, empathy); and (d) *engaged living* (optimism, zest, gratitude), which load onto a higher-order latent trait, *covitality*. Recent evidence on the covitality core psychological strengths indicated that adolescents self-reporting a higher number of strengths were less likely to experience behavioral and emotional problems (Lenzi et al., 2015a) and bullying victimization (Lenzi et al., 2015b) when compared to youth with fewer strengths. These findings suggested the need for capturing a comprehensive picture of students' strengths to foster their synergic effects on students' school and mental health outcomes; however, whether specific combinations of assets are optimally associated with student outcomes has been minimally studied.

Covitality 12 Positive Psychological Assets and Positive Outcomes

Multiple studies support the positive associations of covitality's psychological strengths with healthier student adjustment. For example, self-awareness, self-efficacy, and persistence were associated with academic performance (e.g., Ross & Tolan, 2018; Usher et al., 2019), distress (e.g., Zhang et al., 2013), school connectedness (e.g., Renshaw et al., 2015), and life satisfaction (e.g., Telef & Furlong, 2017). Similarly, peer support, school support (e.g., adult support at school), and family coherence were positively associated with academic achievement, global life satisfaction, and reduced depression (Chen, 2008; Zhang et al., 2013). Additionally, gratitude, optimism, zest, empathy, self-control, and emotional regulation showed positive connections with healthy youth adjustment, such as school connectedness, life satisfaction, and academic achievement, as well as negative associations with distress (e.g., Armenta et al., 2020; Lam, 2020; Ng, 2019; Tangney et al., 2004; Zhen et al., 2021).

Although these studies focused on the positive impact of individual psychological strengths, these strengths were studied in isolation. No research has examined all 12 psychological strengths simultaneously to identify the relative impact of each strength or particular combinations of strengths. Two earlier studies (Lenzi et al., 2015a, 2015b) suggested that possessing more psychological strengths can synergistically affect positive outcomes. However, these studies only focused on the number of strengths and did not examine distinct patterns that may exist across the 12 strength areas. Given that schools have limited time and resources, targeting all 12 strengths at once may not be feasible. Therefore, identifying specific patterns and combinations of assets most relevant to the desired outcomes may be more effective and practical when designing school-based interventions. This study examines students' profiles across 12 psychological strengths and their relations with academic and mental health outcomes. By studying individual strengths in combination, we aim to identify specific patterns to target for interventions to promote positive youth outcomes.

Influences on Youth Strengths

Social and environmental factors contribute to the development of health and well-being and affect youths' access to wellness-promoting resources and opportunities (Held et al., 2020; McPherson & McGibbon, 2010; Viner et al., 2012). Akin to social determinants of health, these social influencers on health and education (SIHE) include, for example, housing in/stability, parental under/employment, food in/security, and social inclusion and non/discrimination (Center for Health and Health Care in Schools [CHHCS], School-Based Health Alliance, National Center for School Mental Health, 2020; Solar & Irwin, 2010). In the USA, SIHEs are distributed such that individuals with historically and multiply minoritized social identities are more likely to live in communities where access to resources and educational, health, and wellness-promoting opportunities has been systematically restricted (McPherson & McGibbon, 2010). In addition to this systemic marginalization, the hostile and stressful environments created by discrimination directed toward youth with minoritized identities impact their well-being and mental health outcomes (Meyer, 2013; Priest et al., 2013). SIHE, thus, can obscure or negatively affect individuals' strengths and well-being (Edyburn et al., 2021).

Although an imperfect metric, students' social identities, such as their race or ethnic identity, gender, or socioeconomic status (SES), can serve as proxy indicators of the effects of SIHE. For example, parent educational attainment (PEA, a metric for SES) is a strong predictor of mental health challenges, likely reflecting access to resources, including mental health care (Reiss, 2013). However, less

research has investigated the relation between SES and indicators of youths' strengths. Research into sex differences in strength indicators has found mixed results, with variation depending on the domain of focus (Romer et al., 2011). Further, whereas measurement invariance was demonstrated among boys and girls on a measure of covitality (Furlong et al., 2022), small to medium-sized effects were found between boys' and girls' latent mean scores on the four second-order strength domains and covitality score (Piqueras et al., 2019; You et al., 2015). This study examines relations between student social identity characteristics—ethnicity, sex, and PEA—and covitality to understand better what factors are associated with student strengths.

Patterns of Youth Covitality

Covitality is a multidimensional construct composed of individual assets that may be present in varying degrees within any individual. When these assets are examined independently or from a unidimensional perspective (e.g., using a total covitality score), relations between strength components and potential variation within second-order domains may be obscured (Kern et al., 2015). Latent profile analysis (LPA) is a person-centered approach to investigate the heterogeneity within a given population (Masyn, 2013; Vermunt, 2004). LPA is an exploratory technique that identifies latent subgroups of youth who, for this study, share similar response patterns among strength indicators (e.g., Masyn, 2013; Petersen et al., 2019). By identifying patterns in individuals' responses to strength indicators, LPA facilitates the examination of strengths' variation across youth populations. Using this approach, we can examine how strength domains relate within or vary across identified subgroups, which subgroups are most common, and how accurately each subgroup represents youths' strengths (Moore et al., 2019a). Further, using LPA, we can identify characteristics that differentiate youth across strength subgroups (e.g., sex) and examine whether the pattern of strengths reflected in each subgroup relates to important outcomes (e.g., academic achievement, life satisfaction). Ultimately, the documentation of distinct patterns of youth strengths, including how these patterns may vary among student characteristics and are differentially related to valued outcomes, may be leveraged to inform strategic wellness promotion efforts (Petersen et al., 2019).

An LPA approach has been applied to investigate potential patterns in youth covitality in several prior studies, each examining covitality as part of a dual-factor mental health framework (Suldo & Shaffer, 2008). Rebelez-Ernst (2015) and Kim et al. (2017) identified covitality and risk profiles separately and then cross-tabulated emerging profiles to form dual-factor mental health groups. Both studies used four second-order domains of covitality (i.e., belief in self, belief in others, emotional competence, and engaged living),

as measured by the Social Emotional Health Survey–Secondary (SEHS-S; Furlong et al., 2014a, 2014b), as indicators in their LPA models. Rebelez-Ernst (2015) identified four latent profiles indicative of very low, below-average, average, and above-average covitality, with similar profiles identified among male and female adolescents. Kim et al. (2017) identified five profiles of covitality among Korean youths (i.e., low, below average, average, above average, and high). Additionally, two recent studies of adolescents (Moore et al., 2019a, 2019b) examined covitality indicators and internalizing and externalizing risk simultaneously. Like the two prior studies, Moore et al., (2019a, 2019b) used the four covitality domains from the SEHS-S and identified four dual-factor mental health profiles. Across these studies, the identified latent profiles were ordered, meaning that patterns of covitality for youth in each profile tended to be similar across domains (e.g., youth in a *low* profile had similarly low levels of belief in self, belief in others, emotional competence, and engaged living). Identified profiles' relations with students' academic and mental health outcomes were also investigated in these previous studies (Kim et al., 2017; Moore et al., 2019a, 2019b; Rebelez-Ernst, 2015). In general, youth in dual-factor mental health profiles characterized by higher levels of covitality and lower levels of risk or distress reported higher life satisfaction, better academic performance, and lower mental health symptoms (e.g., depression, anxiety) or risk-taking behaviors (Kim et al., 2017; Moore et al., 2019a, 2019b; Rebelez-Ernst, 2015).

Limitations of Prior Research

Although existing LPA research provides support for distinct profiles of covitality within adolescent samples, each of these studies examined indicators of covitality via only the four second-order domains of the multidimensional covitality construct. This approach may have obscured variability within and across individual strengths (Kern et al., 2015). For example, a group of students may show low self-awareness from the belief in self domain, low self-control from the emotional competence domain, and low school support from the belief in others domain but have high levels of the remaining nine traits. When examining patterns across only the four second-order domains, this group of students would likely go unidentified and, given their high scores on other traits within the same domain, may instead be classified with other students who have high scores across the four domains. Alternatively, identifying covitality profiles using the 12 specific assets facilitates identifying groups of students with variability across these individual traits. This may provide practical implications for intervention planning, such that individual strengths may be identified as intervention targets. Our study aims to address these limitations of

existing literature by specifying covitality profiles using the 12 strength domains.

Prior research has also provided evidence for the relationship between isolated strengths and indicators of healthy adjustment and has indicated that an accumulation of assets may reduce the likelihood of negative social-emotional outcomes. Further, although previous LPA studies investigated the relation between dual-factor profiles, including covitality indicators, with youth outcomes (Kim et al., 2017; Moore et al., 2019a, 2019b), the relation between covitality profiles with student academic and social-emotional outcomes, independent of students' risk/distress status, was not examined. In addition, only one study reported associations between covitality profiles and student characteristics (sex, ethnicity; Rebelez-Ernst, 2015). Research that examines the relation between covitality-specific profiles with student outcomes and student characteristics is necessary to further inform who comprises identified profiles (Nylund-Gibson & Choi, 2018) and to provide additional evidence about the validity of identified profiles (Petersen et al., 2019).

Current Study

In this study, we (a) used LPA to identify patterns in covitality, as measured by 12 continuous strength domains in a large sample of adolescents in California. To validate the identified profiles, we investigated whether (b) student characteristics, including sex, ethnicity, parent educational attainment (PEA), and grade, were related to profile membership, and (c) identified profiles were differently associated with students' proximal self-reported academic and mental health outcomes (i.e., grades, school connectedness, life satisfaction, and psychological distress). Given prior research, we hypothesized that student characteristics (sex, PEA, and Hispanic/Latino ethnicity) would be significantly associated with profile membership (Rebelez-Ernst, 2015; Reiss, 2013). In our analysis, we focus on Hispanic/Latino ethnicity given that Hispanic/Latino youth comprise over half of the students enrolled in public schools in California (California Department of Education, n.d.) and that Hispanic/Latino youth are the fastest growing group of school-aged students in the USA (National Council of La Raza, 2016). While we recognize the variability in experiences of students who share a Hispanic/Latino background, we anticipated that systematic restriction of SIHE, denoted by a historically marginalized ethnic identity or less socioeconomic privilege, would be associated with profiles indicative of lower covitality. We also hypothesized that profiles would significantly differ in students' proximal academic and mental health outcomes, such that profiles evidencing more psychological assets across domains would be associated with better proximal outcomes (Kim et al., 2017; Moore et al., 2019a, 2019b; Rebelez-Ernst, 2015).

Method

Participants

The sample consisted of 11,217 secondary students from 17 randomly selected California high schools in nine counties. The selected counties represented coastal and inland communities and the state's northern, central, and southern regions; suburban-urban counties in southern California were slightly overrepresented. Students were enrolled in grades 9 ($n=3790$; 33.7%), 10 ($n=2354$; 21.0%), 11 ($n=3237$; 28.9%), and 12 ($n=1846$; 16.5%). Students self-reported their racial and ethnic identification in response to two questions (i.e., "What is your race? (mark all that apply)" and "Are you of Hispanic or Latino origin?"). Participants identified their race as White ($n=4036$; 36.0%), Mixed (two or more races; $n=3885$; 34.6%), Asian ($n=1203$; 10.7%), American Indian/Alaskan Native ($n=622$, 5.5%), Black/African American ($n=429$, 3.8%), Native Hawaiian/Pacific Islander ($n=232$, 2.1%), and no response ($n=810$, 7.2%). Approximately half (48.2%) endorsed a Hispanic/Latino[1] ethnicity. Self-reported sex was male ($n=4237$; 37.8%) or female ($n=4518$; 40.3%). Data regarding students' sex were unavailable for 21.9% ($n=2462$) of the sample due to a discrepancy in how this question was worded for a participating district. Supplementary Table S1 compares this sample to students enrolled in CA public schools; our sample included slightly more girls and was similar in ethnic composition.

Procedure

The data for this study were collected as part of California's ongoing efforts to gather comprehensive school-based surveillance information to monitor school quality indicators. The items in this study were part of the California Healthy Kids Survey (CHKS) administration, administered biennially to students at participating schools and districts (CalSCHLS, 2022). Consistent with CHKS procedures, an introductory letter informed parents of the study and sought permission for their child to take the online survey. Students also had the opportunity to decline to take the survey. School-site administrators coordinated the survey administration. For this study, all students ($N=11,217$) completed the CHKS Core Module (substance use, school safety, school climate) and a second module that included the additional measures

[1] We recognize that many terms have been used to refer to groups of people with Latin American heritage, including Hispanic, Chicano/a, Latino/a, Latinx, and Latine, to be inclusive of individuals with diverse roots/ancestry, the country of origin, spoken language, or gender identity. To be consistent with the way in which students were asked to report their ethnicity on the survey, we use "Hispanic/Latino" throughout this manuscript.

Table 1 Descriptive Statistics of 12 Subdomains of the SEHS-S-2020, Covariates, and Outcomes

	N = 11,217		Missing
	M	SD	n
Latent profile indicators: 12 subdomains			
Self-efficacy	2.96	0.71	0
Self-acceptance	2.96	0.75	0
Persistence	2.35	0.78	0
Social support	3.00	0.84	9
Family coherence	2.90	0.87	0
Peer support	3.08	0.90	0
Emotional regulation	3.08	0.64	0
Empathy	3.11	0.75	2
Self-control	2.85	0.64	0
Optimism	2.60	0.81	0
Zest	2.53	0.84	0
Gratitude	2.85	0.78	0
Covariates			
Sex (female = 1)	.52	.50	2462
Hispanic/Latino ethnicity (Hispanic/Latino = 1)	.48	.50	43
PEA (higher education = 1)	.41	.49	1381
Outcomes			
Self-report grades	5.96	1.70	18
School connectedness	3.49	0.80	3
Psychological distress	2.08	0.85	193
Life satisfaction	4.48	1.05	406

of focus for this study (e.g., covitality, psychological distress, and life satisfaction measures).

Measures

This study's measures included 12 continuous subscales measuring covitality traits, three covariates, and four proximal outcomes described below. Their descriptives are presented in Table 1.

Latent Profile Indicators

Social Emotional Health Survey-Secondary-2020 (SEHS-S-2020) The SEHS-S-2020 (Furlong et al., 2021) is a self-report assessment that measures secondary students' social and emotional strengths. Previous research has supported a three-level higher-order model with one general factor (covitality), four domains, and 12 subscales (self-efficacy, self-awareness, persistence, school support, family coherence, peer support, emotional regulation, empathy, self-control, optimism, gratitude, zest), measured by 36 items. Three items load onto each subscale, and three subscales load onto each domain. Students respond using

a four-point response scale (1 = *not at all true*, 2 = *a little true*, 3 = *pretty much true*, 4 = *very much true*). Reliability for the 12 subdomains ranged from ω = .65–.87, except for self-control (ω = .56). The average scores for the three items measuring each subdomain were used as the indicators in the LPA.

Covariates of Profile Membership

Students' social identity characteristics—sex, Hispanic/Latino ethnicity, PEA—were included in the model as predictors. Given developmental changes observed in students' strengths and well-being across the high-school period (González-Carrasco et al., 2020; Moore et al., 2019b), we also included current grade as a proxy for age as a covariate in the model. Student's sex was assessed via a binary item (i.e., "What is your sex?"), with male (0) and female response options (1). Responses to the question: "Are you of Hispanic or Latino origin?" was used to compare responders with non-Hispanic/Latino (0) and Hispanic/Latino (1) ethnicities. PEA was used to proxy socioeconomic circumstances: parents with some college or less (0) and parents with a university degree or higher (1). The current grade was collapsed into two groups—9th–10th graders (0) and 11th–12th graders (1).

Proximal Outcome Variables

School Connectedness The school connectedness scale has five items assessing students' sense of school belonging and psychological engagement (McNeely et al., 2002). A sample item is, "I feel close to people at this school." Response categories are 1 = *strongly disagree* to 5 = *strongly agree*. Previous research indicates adequate internal consistency (α = .78; Anderman, 2002) with high reliability among students with different ethnic identities (α = .82 to .87: Furlong et al., 2011). Students' average score across the five items was used for this analysis, with higher scores representing elevated school connectedness. The reliability for the current study sample was ω = .83.

Social Emotional Distress Survey-Secondary (SEDS-S, Distress) The SEDS-S (Dowdy et al., 2018) is a 10-item assessment that measures internalizing distress. A sample item is "In the past month, it was hard to get excited about anything." Students respond using a four-point scale (1 = *not at all true*, 2 = *a little true*, 3 = *pretty much true*, and 4 = *very much true*). The SEDS-S has shown a unidimensional factor structure and good concurrent validity (Dowdy et al., 2018). This study used the mean SEDS-S score, with a higher score indicating higher overall distress. The reliability for the current study was ω = .92.

Brief Multidimensional Student Life Satisfaction Scale (Life Satisfaction) Life satisfaction was measured using a five-item student self-report of satisfaction across five domains: family, friends, school, self, and living environment. A sample item is "I would describe my satisfaction with my family life as…" Response categories were from 1 = *very dissatisfied* to 6 = *very satisfied* (Athay et al., 2012). We used the mean total life satisfaction in the analyses. When used with high school students, the scale has shown acceptable internal consistency (α = .75, Funk et al., 2006; α = .83; Ng et al., 2018). Life satisfaction has also shown stable two-week test–retest reliability $r = .91$ (Funk et al., 2006). The reliability for the current study sample was ω = .81.

Self-Report Grades Students reported their usual grades on a scale of 1 = *mostly A's*, 2 = *A's and B's*, 3 = *mostly B's*, 4 = *B's and C's*, 5 = *mostly C's*, 6 = *C's and D's*, 7 = *mostly D's*, and 8 = *mostly F's*. Responses were reverse coded so that higher values indicate better grades.

Statistical Analysis

Latent Profile Analysis (LPA)

To identify students with similar profiles, we estimated a series of LPAs to examine the underlying heterogeneity of the 12 subscales of the SEHS-S-2020. We started by estimating LPA models with 1–10 profiles, increasing the number of profiles by one until the 10-profile solution. Since LPA uses continuous indicators, there is flexibility in specifying the within-profile variance and covariances of the observed indicators. We considered four LPA model specifications (see Masyn, 2013) that vary in the specification of the variance/covariance of the indicators within and across the latent profiles. The *diagonal profile invariant* model specifies that indicator variances are equal across the profiles and that correlations are set to zero among the indicators. The *diagonal profile varying model* freely estimates indicator variances across profiles and sets correlations to zero among the indicators. The *nondiagonal profile invariant model* sets indicator variances to be equal across the profiles and allows correlations to be estimated among the indicators. Finally, the *nondiagonal profile varying model* freely estimates indicator variances for each profile and allows correlations to be estimated among the indicators.

LPA models were estimated using full information maximum likelihood estimation (FIML; Rubin, 1987) in Mplus, Version 8.1 (Muthén & Muthén, 1998–2017). Missingness on any measured items was assumed to be missing at random (MAR), with no built-in reason for systematic missingness; thus, participant scores were not removed unless missing on all items (Nylund-Gibson & Choi, 2018). Multiple random starts helped to ensure that the solution converged on a global rather than a local solution (see Asparouhov & Muthén, 2019).

Profile Enumeration

Based on current recommendations, we used multiple sources of information to guide us on the optimal number of profiles (e.g., Masyn, 2013; Nylund-Gibson & Choi, 2018). The statistical information we considered included two likelihood ratio tests (LRT) and four information criteria (IC). The bootstrapped likelihood ratio test (BLRT; McLachlan & Peel, 2000) and the Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test (VLMR-LRT; Lo et al., 2001) both compare a specified *k*- profile model to a *k*-1 profile model, where a nonsignificant *p*-value indicates the additional *k*- profile model does not improve model fit (Nylund-Gibson & Choi, 2018). Four ICs were used: the approximate weight of evidence (AWE; Banfield & Raftery, 1993), Bayesian information criterion (BIC; Schwarz, 1978), sample size adjusted Bayesian information criterion (SABIC; Sclove, 1987), and the constant Akaike information criterion (CAIC; Bozdogan, 1987). For each IC, lower values and/or diminishing returns when values are plotted (i.e., an elbow after which only small decreases occur for each additional profile) indicate superior model fit (Nylund-Gibson & Choi, 2018). Often, in mixture modeling research (like traditional structural equation modeling), fit statistics alone do not always indicate a singular solution. Recent suggestions from the literature recommend an aggregate approach to exploring and selecting the optimal solution by collectively evaluating fit indices, using substantively based evidence (such as the use of auxiliary variables), and examining the interpretability and utility of the profiles, all of which help reveal to what degree the profiles are classifying and differentiating the considered individuals (Masyn, 2013; Muthén, 2003; Nylund-Gibson & Choi, 2018). Additionally, model parsimony was considered. Finally, entropy was examined for the chosen model to assess the overall accuracy of classification as a substantive check (Nylund-Gibson & Choi, 2018). Entropy values above .80 and closer to 1.00 indicate superior classification precision (Masyn, 2013).

Covariates and Proximal Outcomes

After deciding the number of profiles, we included covariates and proximal outcomes to explore relations among the identified latent profiles using the recommended ML 3-step method (Vermunt, 2010). The ML 3-step allows covariates' and outcomes' relations to be simultaneously estimated (see Asparouhov & Muthén, 2014; Nylund-Gibson et al., 2019) while preserving the measurement of the latent profiles. Using this approach, we specified an LPA model with auxiliary variables, as depicted in Supplementary Fig. S1. In

this model, we simultaneously estimated the relation of the four covariates ($x \rightarrow C$) and four outcome variables ($C \rightarrow d$) with the latent profile variable, controlling for the direct relationship between the covariate and the proximal outcomes ($x \rightarrow d$; see Supplementary Material for $x \rightarrow d$ results).

Multinomial logistic regression was used for the relations between the covariates and the latent profile variable, whereby the categorical latent variable is regressed on the covariates. The estimated logit coefficients, odds ratios, and the 95% confidence interval were used to understand the relations. Specifically, we evaluated the likelihood of being in one profile over a reference profile based on a one-unit change in the covariate.

We estimated conditional means for each latent profile to evaluate the latent profiles' and outcomes' relations. The overall relation was first evaluated using an omnibus Wald test and an effect size measure (LTB-ω; Lanza et al., 2013) based on Cohen's *d* metric. If there was evidence of a strong relation (e.g., a significant Wald test and/or an LTB-ω value > .20), then all pairwise comparisons across the profile-specific means of the proximal outcomes were estimated (Asparouhov & Muthén, 2014). Outcome mean differences were estimated, and effect sizes were calculated to interpret the size of the difference to account for our large sample size. The strength of each mean difference was evaluated using Cohen's (1992) recommendation of no effect ($d = 0.00$), small effect ($d = 0.20$), medium effect ($d = 0.50$), or large effect ($d \geq 0.80$).

Results

Covitality Profile Enumeration

LPAs were estimated using the 12 SEHS-S-2020 (Furlong et al., 2021) subdomain means for the four variance/covariance model specifications. Fit information for enumeration models with 1 through 10 profiles is available in Supplementary Table S3. Results for the diagonal profile invariant model, the default covariance structure in M*plus*, are considered. The LPA models with the three other variance/covariance structures did not yield improved fit or parsimony and encountered convergence issues. The BIC, SABIC, and CAIC decreased with each additional profile, with the AWE having the lowest value at the 9-profile model. So, we considered the scree plot of IC values (Supplementary Fig. S2), looking for where there is a flattening out. All ICs began to flatten out at the 4-profile model, indicating a minimal increase in model fit for each additional profile. The VLMR-LRT and BLRT did not achieve a nonsignificant *p*-value through all 10 models; thus, they did not support any solution.

Given the lack of agreement among fit indicators to support a single profile solution, we relied on the BIC, supplemented with other IC, when narrowing down candidate solutions (Nylund-Gibson & Choi, 2018; Nylund-Gibson & Masyn, 2016). When examining the addition of profiles using a scree plot (Fig. S2), the BIC (and other IC) had diminishing returns beginning around the 3-profile model, with a smaller elbow observed at the 5-profile solution. Thus, the 3-, 4-, and 5-profile models were all examined with the auxiliary variables to allow for substantive checking of the interpretability and meaningfulness of identified profiles with external variables (Muthén, 2003). The 3- and 4-profile solutions indicated significant differences between identified profiles and auxiliary variables. There were fewer significant differences between identified profiles for the outcome mean comparisons and covariate comparisons for the 5-profile model. Using this evidence, along with the diminishing return by the BIC (and all IC, see Fig. S2) and considerations regarding the parsimony of identified solutions, the 4-profile model was chosen as the final LPA model. The 4-profile model showed excellent classification accuracy with an entropy of .85.

The identified profiles were ordered and labeled in reference to each other (see Fig. 1). The four profiles were *High* ($n = 2354$, 21.1%), *Moderate-High* ($n = 4608$, 41.4%), *Moderate-Low* ($n = 3251$, 29.2%), and *Low* ($n = 929$, 8.3%) *Covitality*. Mean values of the 12 subdomains ranged from $M = 3.1$ to $M = 3.7$ for the *High* profile, $M = 2.4$ to $M = 3.2$ for the *Moderate-High* profile, $M = 2.0$ to $M = 2.9$ for the *Moderate-Low* profile, and $M = 1.5$ to $M = 2.3$ for the *Low* profile. Patterns of the identified profiles revealed that mean persistence scores were visually lower across the profiles, and mean empathy, emotional regulation, and self-control scores were higher among the lower profiles. Notably, there was a decrease in mean values of optimism, zest, and gratitude among the lower profiles.

Covariates in Covitality LPA

Multinomial logistic regression investigated differences across the four latent profiles by comparing the covariates (sex, Hispanic/Latino ethnicity, PEA, and grade level). To facilitate the comparison across all the latent profiles and covariate relations, we present the results with multiple reference profiles in Table 2. Results for student's sex indicated that females were more likely than males to be in the *Moderate-Low* profile ($logit = 0.34$, $p < .001$, $OR = 1.40$) and the *Low* profile ($logit = 0.28$, $p = .011$, $OR = 1.32$) compared to the *High* profile. Females were also more likely than males to be represented in the *Moderate-Low* profile ($logit = 0.21$, $p = .001$, $OR = 1.24$) compared to the *Moderate-High* profile. There were no significant differences for sex when

Fig. 1 Mean Profile Plots for the Four-Profile LPA Model. *Note.* Response categories are 1 = not at all true, 2 = a little true, 3 = pretty much true, 4 = very much true. Shaded areas represent the four SEHS-S-2020 domains (Color figure online)
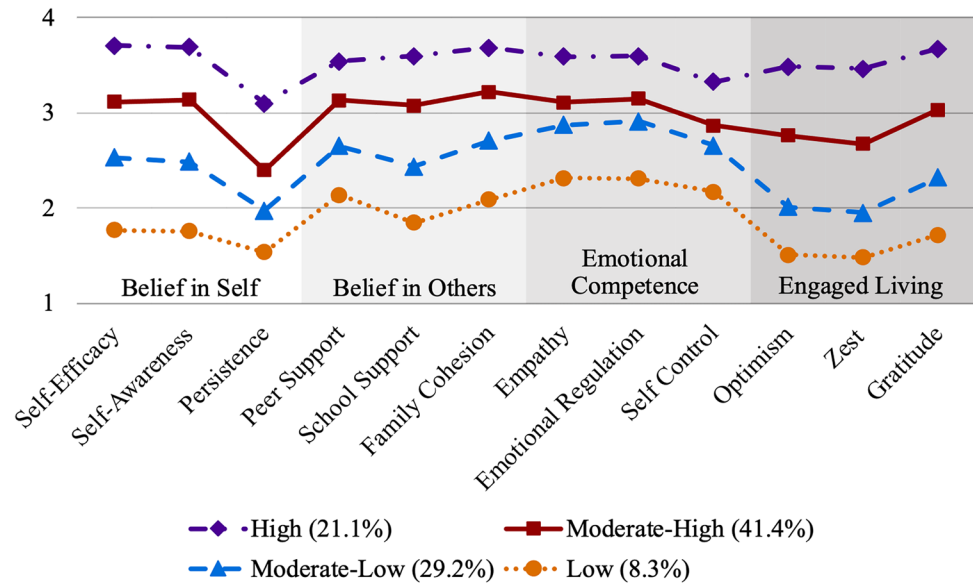

Table 2 Logit, odd ratios, and confidence intervals for all pairwise comparisons relating the latent profile variable to the covariates of sex, Hispanic/Latino ethnicity, and parent educational attainment

| | | Comparison profile | | | | | | | | |
| | | High covitality | | | Moderate-high covitality | | | Moderate-low covitality | | |
Profile	Effect	Logit	OR	OR [95% CI]	Logit	OR	OR [95% CI]	Logit	OR	OR [95%CI]
Moderate-high	Female	0.12	1.13	[0.99, 1.30]	–	–	–	–	–	–
	Hispanic/Latino	0.03	1.03	[0.89, 1.18]	–	–	–	–	–	–
	PEA	− 0.20**	0.82	[0.71, 0.95]	–	–	–	–	–	–
	Grade level	0.07*	1.07	[1.00, 1.14]	–	–	–	–	–	–
Moderate-low	Female	0.34***	1.40	[1.22, 1.61]	0.21**	1.24	[1.09, 1.41]	–	–	–
	Hispanic/Latino	0.02	1.02	[0.88, 1.18]	− 0.01	0.99	[0.87, 1.13]	–	–	–
	PEA	− 0.43***	0.65	[0.56, 0.76]	− 0.23**	0.79	[0.69, 0.91]	–	–	–
	Grade level	0.05	1.05	[0.98, 1.12]	− 0.02	0.98	[0.93, 1.04]	–	–	–
Low	Female	0.28*	1.32	[1.07, 1.64]	0.16	1.17	[0.96, 1.43]	− 0.06	0.95	[0.76, 1.18]
	Hispanic/Latino	0.10	1.12	[0.89, 1.38]	0.08	1.08	[0.88, 1.33]	0.09	1.09	[0.87, 1.37]
	PEA	− 0.74***	0.48	[0.38, 0.61]	− 0.54***	0.59	[0.46, 0.73]	− 0.31*	0.74	[0.57, 0.95]
	Grade Level	− 0.00	1.00	[0.91, 1.10]	− 0.06	0.94	[0.86, 1.02]	− 0.05	0.96	[0.87, 1.05]

PEA = Parent Educational Attainment

*p < .05. **p < .01. ***p < .001

comparing all other profiles. Overall, female students were more likely to be in the profiles with lower covitality.

Results for PEA indicated that students who had parents with more educational attainment were less likely to be in the *Moderate-High* profile ($logit = − 0.20, p = .007$, $OR = 0.82$), *Moderate-Low* profile ($logit = − 0.43, p < .001$, $OR = 0.65$), and the *Low* profile ($logit = − 0.74, p < .001$, $OR = 0.48$) than the *High* profile compared to students who reported their parents had less educational attainment. Students who reported their parents to have more educational attainment were less likely to be in the *Low* profile than the *Moderate-High* ($logit = − 0.54, p = .001, OR = 0.59$)

and the *Moderate-Low* profile ($logit = − 0.23, p = .001$, $OR = 0.79$) compared to students whose parents had less educational attainment. Further, students who reported their parents to have more educational attainment were less likely to be in the *Low* profile than the *Moderate-Low* profile ($logit = − 0.31, p = .017, OR = 0.74$) than those reporting their parents had less educational attainment. The pattern for PEA indicated that students whose families have higher socioeconomic status, as measured by parents' higher educational attainment, were more likely to be in the higher Covitality profiles.

Table 3 Outcome means for each profile, differences, and Cohen's d for each comparison

Outcome	LTB-ω	Profile	μ	SD		Comparisons					
						$\mu_1–\mu_2$	$\mu_2–\mu_3$	$\mu_3–\mu_4$	$\mu_1–\mu_3$	$\mu_2–\mu_4$	$\mu_1–\mu_4$
Self-report grades	0.48	1. High	5.91	1.40	μ_{diff}	0.34	0.58	0.64	0.91	1.21	1.55
		2. Moderate-High	5.58	0.76							
		3. Moderate-low	5.00	0.81	Cohen's d	0.23	0.36	0.35	0.57	0.78	1.01
		4. Low	4.37	0.50							
School connectedness	0.43	1. High	4.48	1.48	μ_{diff}	0.37	0.57	0.38	0.94	0.95	1.32
		2. Moderate-high	4.11	0.58							
		3. Moderate-low	3.54	0.72	Cohen's d	0.58	0.98	0.50	1.21	1.55	1.72
		4. Low	3.17	0.60							
Distress	0.36	1. High	1.36	1.75	μ_{diff}	−0.24	−0.57	−0.14	−0.82	−0.71	−0.96
		2. Moderate-high	1.60	0.75							
		3. Moderate-low	2.18	0.79	Cohen's d	0.32	0.76	0.17	1.02	0.95	1.15
		4. Low	2.32	0.86							
Life satisfaction	0.79	1. High	5.83	1.96	μ_{diff}	0.61	0.99	0.91	1.61	1.90	2.52
		2. Moderate-high	5.22	0.79							
		3. Moderate-low	4.23	0.92	Cohen's d	1.08	1.44	1.08	2.34	2.77	3.91
		4. Low	3.32	1.04							

LTB-ω = Lanza, Tan, and Bray omega. Response categories for the scales are as follows: Self-Report Grades – 1 = *mostly F's* to 8 = *mostly A's*; School Connectedness – 1 = *strongly disagree* to 5 = *strongly agree*; Distress – 1 = *not at all true* to 4 = *very much true*; and Life Satisfaction – 1 = *very dissatisfied* to 6 = *very satisfied*

Grade level was not consistently related to covitality profiles. Students in the 11th and 12th grades were more likely to be in the *Moderate-High* profile (logit = − 0.07, $p = .042$, OR = 1.07) than the *High* profile compared to students in the 9th and 10th grades. However, there were no significant grade-level differences when comparing all other profiles. There were no significant differences across the profiles for Hispanic/Latino or non-Hispanic/Latino ethnicities.

Outcome Differences Across Profiles

Omnibus Tests

Before investigating the pairwise comparisons of outcome means (self-report grades, school connectedness, distress, and life satisfaction) across the profiles, we first explored whether there were associations between the latent profiles and the proximal outcomes using an omnibus test and LTB-ω (see Table 3). Significant Wald tests and meaningful effect sizes were observed for all outcome variables: *self-report grades*, $\chi^2(3) = 440.63$, $p < .001$, LTB-ω = 0.48; *school connectedness* $\chi^2(3) = 1648.71$, $p < .001$, LTB-ω = 0.43; *distress* $\chi^2(3) = 1121.61$, $p < .001$, LTB-ω = 0.36; and *life satisfaction* $\chi^2(3) = 4898.00$, $p < .001$, LTB-ω = 0.79. Thus, there was support for investigating where differences emerge using pairwise comparisons.

Outcome Mean Differences

Results for outcome mean differences and their associated Cohen's d range are presented in Table 3. All pairwise comparisons were significant ($p < .01$). Looking across self-reported grades, school connectedness, distress, and life satisfaction, student profiles characterized by higher levels of covitality across strength domains tended to have more optimal outcomes. The *High* profile had the highest self-report grades with a mean value just below the *mostly B's* category ($M = 5.91$), whereas the *Low* profile had the lowest self-report grades with the mean value falling within the *mostly B's and C's category* ($M = 4.47$, $d_{range} = 0.23$ to 1.01; see supplementary material Fig. S3, Panel A). Similarly, for school connectedness (see Fig. S3, Panel B), those in the *High* profile had the highest scores with the mean value in the center of the *agree* category ($M = 4.48$). The *Low* profile had the lowest scores with the mean value near the bottom of the *neither disagree or agree* category ($M = 3.17$, $d_{range} = 0.50$ to 1.72). Results for psychological distress (see Fig. S3, Panel C) indicated lower scores in the *High* profile with a mean value falling between the *not at all true* and *a little true* categories ($M = 1.36 \approx$ *not at all true*). In comparison, the *Low* profile had a mean value between *a little true* and *pretty much true* categories ($M = 2.32$, $d_{range} = 0.17$ to 1.15), suggesting those with higher covitality report lower distress. For life satisfaction (see Fig. S3, Panel D), those in the *High* profile reported the highest scores, with the

mean value falling between the *very satisfied* and the *satisfied* categories ($M = 5.83$). The lowest score was reported by those in the *Low* profile, with the mean value within the *a little dissatisfied* category ($M = 3.32$, $d_{range} = 1.08$ to 3.91). Results indicated that higher covitality is associated with higher overall life satisfaction.

Cohen's *d* estimates for the pairwise comparisons ranged from no effect to large effect sizes. Generally, the largest effect sizes were between the *High* and *Moderate-Low* profiles, except for self-reported grades, where the largest effect was between the *High* and *Low* profiles. Across proximal outcomes, the most pronounced differences among covitality profiles were observed for life satisfaction.

Discussion

Supporting student competencies across various positive psychological domains is essential for promoting their mental health and well-being (Suldo & Shaffer, 2008; World Health Organization, 2016). This study identified latent profiles of adolescents' covitality using 12 continuous psychological strength indicators (Furlong et al., 2014). We further examined how students' social identity characteristics were related to profile membership and how the profiles related to proximal student outcomes, including self-reporting of grades, school connectedness, psychological distress, and life satisfaction.

Identified Covitality Profiles

Results of LPA supported an ordered (i.e., no overlap between profiles across the 12 indicators) four-profile solution, including profiles characterized by *High, Moderate-High*, *Moderate-Low*, or *Low Covitality*. Most students were represented in the *Moderate-High* profile (41.4%), followed by the *Moderate-Low* profile (29.2%), with the fewest students in the *Low* profile (8.3%). The number of profiles and the general pattern in profile proportions found in this study are consistent with the findings of prior research that examined covitality profiles across four broader covitality domains (Moore et al., 2019a, 2019b; Rebelez-Ernst, 2015; of note, Kim et al. (2017) identified five covitality profiles among a sample of Korean students), indicating that similar covitality profiles are likely to be observed across a variety of adolescent populations.

The ordered profile pattern across the 12 indicators demonstrates that the positive psychological constructs underlying covitality are conceptually related and co-occur in adolescents (Renshaw et al., 2014). The relative similarity in mean values for most of the 12 strength indicators within each profile suggests that these positive psychological strengths may develop in tandem, such that the development

of strengths in one covitality indicator may contribute to, or be supported by, the development of strengths in another domain (Rebelez-Ernst, 2015). Indeed, ordered profile solutions are common when specifying mixture models on highly correlated indicators, as with the covitality indicators used in this and prior research (Furlong et al., 2021; Nylund-Gibson & Choi, 2018). However, our examination of 12 covitality strength domains revealed important variation across indicators that could not be observed in prior studies solely examining the four second-order covitality domains (i.e., belief in self, belief in others, emotional competence, and engaged living). First, the persistence subscale tended to have one of the lowest average means for each profile, even in profiles characterized by high levels of the other strength domains. Second, considering the four second-order domains examined in prior research, we observed greater separation between the profiles' mean scores across the indicators in the belief in self and engaged living domains (see Fig. 1). In contrast, there was less differentiation between profiles across indicators in the emotional competence domain, with mean scores being remarkably similar for the *Moderate-High* and *Moderate-Low* covitality profiles. This finding suggests that indicators within the domains of belief in self and engaged living may be superior in differentiating levels of student strengths as conceptualized via covitality. As these indicators could provide better discrimination across strength profiles, future research and practice may examine the utility of using scores from scales in these domains when assessing students for their strength levels.

Profiles' Relations with Student Characteristics and Proximal Outcomes

Students' social identity characteristics, precisely their PEA and sex, were significantly associated with covitality profile membership, whereas Hispanic/Latino ethnicity was not. However, the magnitude of the resulting odds ratios for these effects was relatively small (Chen et al., 2009). Looking across covitality profiles, students with abundant socioeconomic resources, as indicated by higher levels of PEA, were more likely to be represented by profiles characterized by higher levels of covitality across indicators. The relation between socioeconomic circumstances and access to wellness-promoting opportunities and resources (e.g., housing and food security, parental employment, high-quality schools, and community health infrastructure) is well documented (Devenish et al., 2017; Travis & Leech, 2013). Thus, the higher levels of covitality observed among students with more PEA may indicate their access to additional resources conferred by their socioeconomic status. Also consistent with prior research, females were more likely than males to be in the *Moderate-Low* and *Low* covitality profiles (Piqueras et al., 2019),

with these differences being small (You et al., 2015). However, females were rated to have more social-emotional strengths on other measures (e.g., Romer et al., 2011). Additional research is needed to understand what mechanisms contribute to the observed relations between sex with students' covitality. Finally, although student grade level was also not consistently associated with covitality profiles, students in the 11th and 12th grades were more likely to be in the *Moderate-High* than the *High* profile compared to 9th and 10th-grade students. This finding is partially consistent with prior research demonstrating variability in adolescents' dual-factor mental health across high school (Moore et al., 2019b) and declines in subjective well-being across adolescence (González-Carrasco et al., 2020).

Consistent differences were identified across covitality profiles for the student proximal outcomes of grades, school connectedness, psychological distress, and life satisfaction—providing evidence that the emerging profiles are distinct. The overall trend indicated that adolescents in profiles characterized by higher levels of covitality across indicators tended to report significantly higher grades, more feelings of connectedness at school, greater life satisfaction, and less distress; students in the *High* covitality profile reported the most favorable proximal outcomes. These findings support prior research investigating the configuration of youths' developmental assets. Consistent with Lenzi et al. (2015a, 2015b), we found that adolescents in profiles with higher levels of covitality across indicators tended to experience less adverse outcomes, such as lower levels of psychological distress (i.e., internalizing symptoms). We extend this research by providing evidence that these students tended to experience more positive proximal mental health outcomes (i.e., life satisfaction and school connectedness). These positive mental health outcomes have been less emphasized in prior research yet are critical for understanding and promoting a comprehensive view of students' mental health (e.g., Grych et al., 2020).

We observed the largest effect sizes for mean differences between identified covitality profiles for life satisfaction. This finding emphasizes the critical role of covitality constructs in students believing that their life is going well and being satisfied. Fredrickson's (2013) broaden-and-build theory suggests that positive emotions will broaden and build one's mind, skills, and resources, ultimately leading to greater well-being. Thus, interventions that promote students' social-emotional assets may help adolescents develop positive psychosocial skills and resources and experience an overall positive appraisal of life satisfaction. Recognizing that individual strengths may reflect the availability of social and environmental resources and opportunities (e.g., Mahdiani & Ungar, 2021), addressing

systemic marginalization and building affirming and healing educational institutions is also critical.

Limitations and Future Directions

This study's results are interpreted within the context of its limitations. As is common with applications of mixture models, it was difficult to distinguish candidate profile solutions using statistical fit criteria, which did not agree on a single solution. Aligned with best practice recommendations, we used a combination of statistical and substantive fit criteria during the profile enumeration process. We considered solutions' interpretability, meaningfulness when examining outcomes and covariates, and parsimony before deciding to move forward with the 4-profile solution (e.g., Nylund-Gibson & Choi, 2018). These results, therefore, should be considered as one possible solution to understanding patterns in covitality and other approaches (e.g., *k*-mean cluster) may yield meaningful insights. Our large sample meant that we had small standard errors, giving us greater power to detect statistically significant differences in our auxiliary analyses; all *statistically* significant effects may not be *practically* significant. Thus, we focused on effect sizes in our interpretation of significant results. Although our sample included students enrolled in a random sample of California schools in suburban-urban and rural areas, our sample may not represent students at the national level. Future research should include nationally representative samples to improve the generalizability of the findings.

Although our approach was consistent with prior research examining patterns of covitality as part of a dual-factor mental health framework, different patterns of adolescents' covitality and their relation to proximal student outcomes may have been observed had we measured covitality differently in this study. For example, the ordered profiles observed in this study and prior research may be an artifact of the single-informant self-report format of the 12 indicators measured on the SEHS-S or reflect another limitation of the measure. Informant disagreement has been well-documented for assessments of psychosocial functioning, and a multi-informant approach is recommended for understanding youth functioning across contexts (e.g., De Los Reyes et al., 2019; Herman et al., 2018). Future studies that include indicators that capture the perspectives of multiple informants (i.e., students, teachers, and/or caregivers) may identify nonordered or otherwise different covitality patterns and better illuminate students' strengths across settings. Another limitation of the measure is the low-reliability estimate found for the self-control subscale. In other studies using this measure (Piqueras et al., 2019) the reliability of the self-control subscale has typically been lower than other subscales, indicating that revision of this subscale may be warranted.

The higher education version of the SEHS (Furlong et al., 2016), replaced the self-control subscale with a cognitive reappraisal subscale, which yielded more robust psychometric properties (Furlong et al., 2021). Similar refinements may be appropriate for the secondary version of the SEHS.

Notably, the 12 psychosocial assets of covitality reflect aspects of an individual's social environment (i.e., perceived support from peers, family, and school) and characteristics often interpreted as internal assets (e.g., persistence, emotion regulation, optimism). However, any assessment of an individual's strengths must be understood within the social and environmental contexts and systems that affect development and what is considered a strength (Mahdiani & Ungar, 2021). The observed covitality patterns may reflect variation in individual assets, in youths' contexts that support/hinder strengths or well-being, or a combination of both. Although we attempted to consider the influence of context on patterns of covitality in this study through indicators of students' social identities, these are imperfect and limited metrics of the environmental conditions that shape wellness. We recommend that future studies directly assess social and environmental contexts that promote, hinder, or obscure strengths (e.g., see CHHCS et al., 2021). Researchers might examine whether strength profiles vary based on measures of an individual's social and environmental context collected via these assessments or provided in publicly available data (e.g., Child Opportunity Index; Acevedo-Garcia et al., 2020). Future research into adolescent strengths patterns should also include indicators representing individual, social, family, school, and systemic factors that support well-being and positive youth outcomes.

Additionally, the student demographic variables of PEA and student sex were dichotomized for use as covariates in this study, and data regarding students' sex were not available for approximately 22% of the sample due to a discrepancy in how this question was worded for a participating district. However, sensitivity analysis revealed identical profile patterns for students for whom data regarding sex responses were unavailable, suggesting that these missing data would not have significantly augmented our findings regarding the relation between sex and covitality profiles. It will be essential to include more sensitive and inclusive measures (e.g., nonbinary measures of students' gender identity) in future research. The variables used in this research were also measured concurrently. Therefore, we could not specify the directionality of profiles' relations with proximal student outcomes—shared-method variance may have inflated the observed associations. Future research should leverage a multi-method approach and more objective indicators (e.g., grades reported in school records, observational data). Unfortunately, matched student and teacher data were unavailable in the anonymous surveys administered for this study.

Implications and Conclusion

Integrating strength indicators into school-based assessment and mental health conceptualizations is increasingly essential in contemporary school mental health research and practice (Nickerson & Fishman, 2013; Suldo & Shaffer, 2008). Covitality, representing the synergistic and interconnected nature of psychological assets, is associated with important academic and mental health outcomes and strongly relates to students' life satisfaction. Given these relationships, incorporating covitality into strength-based assessment practices can indicate which students are thriving and which may benefit from additional support in these outcome domains. Results of this study, combined with the results of other studies investigating profiles of covitality, suggest that broader (i.e., four domains instead of 12 assets) and perhaps briefer (i.e., one item per asset instead of three items or reduced items across each domain) measures may be sufficient to identify students with high, moderate, or low covitality profiles. As such, if the goal is screening to identify which students may have higher or lower levels of covitality to inform prevention or intervention efforts, shorter measures of the constructs assessing covitality may be sufficient. A brief version of the SEHS-S may be beneficial for use within a school-based dual-factor mental health screening practice.

When integrated into universal screening practices covitality may provide helpful information for guiding universal wellness promotion practices and for identifying students who may benefit from additional tiered supports (Moore et al., 2015; Furlong et al., 2022). As part of a multi-tiered intervention framework, wellness-focused interventions rooted in the principles of positive psychology may be integrated into school curricula at a universal level to support all students. For example, psychoeducation curricula designed to promote student happiness (e.g., Suldo, 2016) may be implemented universally within schools to enhance covitality-related constructs such as gratitude and optimism; universal curricula designed to enhance student strengths have been shown to improve meaningful outcomes, including students' subjective well-being and life satisfaction (Roth et al., 2017; Suldo et al., 2014). Since persistence was the lowest individual covitality indicator in all identified profiles, universal school-based interventions may specifically target persistence among adolescents. Recent studies suggest several evidence-based strategies for improving persistence, including adults being patient with students instead of quickly taking over challenging tasks, modeling persistence, noticing and praising students' efforts when they persist through a difficult task, and helping to break down challenging tasks into smaller, more manageable goals (e.g., Gunderson et al.,

2013; Leonard et al., 2020, 2021). In addition to universal supports, students fitting *Low* or *Moderate* covitality profiles may be potential candidates for more intensive prevention and early intervention.

The ordered pattern of results observed across research applying LPA to investigate covitality suggests that strength-based universal programming that targets an individual covitality trait (e.g., persistence) or one of four broader domains (e.g., belief in self) may be effective in synergistically promoting other individual traits or domains of covitality; these covitality indicators are highly correlated and may promote each other. Although general interventions focused on building strengths across domains may promote adolescents' covitality and support positive outcomes (Lenzi et al., 2015a, 2015b), it may not be practical or realistic to suggest interventions to target all 12 covitality indicators at once. For example, persistence interventions may improve other covitality indicators, such as self-esteem, emotional regulation, and optimism, as they correlate and develop together.

An accumulating body of research suggests a significant positive association between covitality and academic and mental health outcomes. However, research is needed to examine how students' social, family, and school contexts support or hinder the strengths comprising covitality. While individual interventions can help to build students' competencies across covitality domains, we must also be cognizant of social and environmental influencers that can promote or hinder the development or demonstration of these strengths. Instead of a singular focus on remediating deficits in students' strengths, school mental health professionals must work to change school systems to be more supportive of students' mental health and well-being (Meyer, 2013; Moore et al., 2023). Ultimately, it will be necessary for these efforts to reflect culturally and contextually informed conceptualizations of what constitutes a strength or asset and to include processes for identifying and integrating community/cultural assets into school systems and models of student strengths (Mahdiani & Ungar, 2021; Moore et al., 2023).

Declarations

References

Acevedo-Garcia, D., Noelke, C., & McArdle, N. (2020). *The geography of child opportunity: Why neighborhoods matter for equity.* Findings from the child opportunity index 2.0. https://bit.ly/3QGbQi8

Anderman, E. M. (2002). School effects on psychological outcomes during adolescence. *Journal of Educational Psychology, 94*(4), 795–809. https://doi.org/10.1037/0022-0663.94.4.795

Armenta, C. N., Fritz, M. M., Walsh, L. C., & Lyubomirsky, S. (2020). Satisfied yet striving: Gratitude fosters life satisfaction and improvement motivation in youth. *Emotion, 22*(5), 1004–1016. https://doi.org/10.1037/emo0000896

Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural*

Equation Modeling: A Multidisciplinary Journal, 21(3), 329–341. https://doi.org/10.1080/10705511.2014.915181

Asparouhov, T., & Muthén, B. (2019). *Random starting values and multistage optimization*. Muthén & Muthén, Mplus. https://www.statmodel.com/download/StartsUpdate.pdf

Athay, M. M., Kelley, S. D., & Dew-Reeves, S. E. (2012). Brief Multidimensional Students' Life Satisfaction scale—PTPB version (BMSLSS-PTPB): Psychometric properties and relationship with mental health symptom severity over time. *Administration and Policy in Mental Health and Mental Health Services Research, 39*(1–2), 30–40. https://doi.org/10.1007/s10488-011-0385-5

Banfield, J. D., & Raftery, A. E. (1993). Model-based Gaussian and non-Gaussian clustering. *Biometrics, 49*, 803–821. https://doi.org/10.2307/2532201

Bozdogan, H. (1987). Model selection and Akaike's information criterion (AIC): The general theory and its analytical extensions. *Psychometrika, 52*, 345–370. https://doi.org/10.1007/bf02294361

California Department of Education. (n.d.). 2017–2018 enrollment by ethnicity and grade. California Department of Education Data Quest. [2023, November 9]. https://bit.ly/40DKL3P

CalSCHLS (2022). *Survey administration*. https://calschls.org/survey-administration/

Center for Health and Health Care in Schools [CHHCS], School-Based Health Alliance, National Center for School Mental Health (2020). *Understanding social influencers of health and education: A role for school-based health centers and comprehensive school mental health systems*. School Health Services National Quality Initiative. https://bit.ly/3sFQpWv

Center for Health and Health Care in Schools, School-Based Health Alliance, National Center for School Mental Health (2021). *Assessing social influencers of health and education*. School Health Services National Quality Initiative. https://bit.ly/49Geptq

Chen, H., Cohen, P., & Chen, S. (2009). How big is a big odds ratio? Interpreting the magnitudes of odds ratios in epidemiological studies. *Communications in Statistics-Simulation and Computation, 39*(4), 860–864. https://doi.org/10.1080/03610910903650383

Chen, J. J. (2008). Grade-level differences: Relations of parental, teacher and peer support to academic engagement and achievement among Hong Kong students. *School Psychology International, 29*(2), 183–198. https://doi.org/10.1177/0143034308090059

Cicchetti, D., & Cohen, D. J. (Eds.). (2006). *Developmental psychopathology: Theory and method* (2nd ed.). John Wiley & Sons, Inc.

Cohen, J. (1992). Statistical power analysis. *Current Directions in Psychological Science, 1*(3), 98–101. https://doi.org/10.1111/1467-8721.ep10768783

De Los Reyes, A., Cook, C. R., Gresham, F. M., Makol, B. A., & Wang, M. (2019). Informant discrepancies in assessments of psychosocial functioning in school-based services and research: Review and directions for future research. *Journal of School Psychology, 74*, 74–89. https://doi.org/10.1016/j.jsp.2019.05.005

Devenish, B., Hooley, M., & Mellor, D. (2017). The pathways between socioeconomic status and adolescent outcomes: A systematic review. *American Journal of Community Psychology, 59*(1–2), 219–238. https://doi.org/10.1002/ajcp.12115

Dowdy, E., Furlong, M. J., Nylund-Gibson, K., Moore, S., & Moffa, K. (2018). Initial validation of the Social Emotional Distress Survey-Secondary to support complete mental health screening. *Assessment for Effective Intervention, 43*(4), 241–248. https://doi.org/10.1177/1534508417749871

Edyburn, K. L., Berone, A., Raines, T. C., Hinton, T., Twyford, J., & Dowdy, E. (2021). Integrating intersectionality, social determinants of health, and healing: A new training framework for school-based mental health. *School Psychology Review, 52*, 563–585. https://doi.org/10.1080/2372966X.2021.2024767

Fredrickson, B. L. (2013). Updated thinking on positivity ratios. *American Psychologist, 68*(9), 814–822. https://doi.org/10.1037/a0033584

Funk, B. A., Huebner, E. S., & Valois, R. F. (2006). Reliability and validity of a brief life satisfaction scale with a high school sample. *Journal of Happiness Studies, 7*(1), 41–54. https://doi.org/10.1007/s10902-005-0869-7

Furlong, M. J., Dowdy, E., Carnazzo, K., Bovery, B., & Kim, E. (2014a). Covitality: Fostering the building blocks of complete mental health. *Communiqué, 42*(8), 28–29.

Furlong, M. J., Dowdy, E., Moore, S., & Kim, E. (2022). Adapting the dual-factor model for universal school-based mental health screening: Bridging the research to practice divide. In K.-A. Allen, M. J. Furlong, S. Suldo, & D. Vella-Brodrick (Eds.), *Handbook of positive psychology in schools: In support of positive educational processes*, 3rd edn., Taylor & Francis.

Furlong, M. J., Dowdy, E., Nylund-Gibson, K., Wagle, R., Carter, D., & Hinton, T. (2020). Enhancement and standardization of a universal social-emotional health measure for students' psychological strengths. *Journal of Well-Being Assessment, 4*, 245–267. https://doi.org/10.1007/s41543-020-00032-2

Furlong, M. J., O'Brennan, L. M., & You, S. (2011). Psychometric properties of the Add Health school connectedness scale for 18 sociocultural groups. *Psychology in the Schools, 48*(10), 986–997. https://doi.org/10.1002/pits.20609

Furlong, M. J., Piqueras, J. A., Chacón-Gutiérrez, L., Dowdy, E., Nylund-Gibson, K., Chan, M., Soto-Sanz, V., Marzo, J. C., Rodríguez-Jiménez, T., & Martínez-González, A. E. (2021). Assessing college students' social and emotional strengths: A cross-cultural comparison from Mexico, United States, and Spain. *European Journal of Psychology and Educational Research, 4*(2), 123–137. https://doi.org/10.12973/ejper.4.2.123

Furlong, M. J., You, S., Renshaw, T. L., Smith, D. C., & O'Malley, M. D. (2014b). Preliminary development and validation of the social and emotional health survey for secondary school students. *Social Indicators Research, 117*(3), 1011–1032. https://doi.org/10.1007/s11205-013-0373-0

Furlong, M. J., You, S., Shishim, M., & Dowdy, E. (2016). Development and validation of the Social Emotional Health Survey-Higher Education version. *Applied Research in Quality of Life, 2*, 343–367. https://doi.org/10.1007/s11482-016-9464-9

González-Carrasco, M., Sáez, M., & Casas, F. (2020). Subjective well-being in early adolescence: Observations from a five-year longitudinal study. *International Journal of Environmental Research and Public Health, 17*(21), 8249. https://doi.org/10.3390/ijerph17218249

Grant, K. E., Compas, B. E., Thurm, A. E., McMahon, S. D., Gipson, P. Y., Campbell, A. J., Krochock, K., & Westenholm, R. I. (2006). Stressors and child and adolescent psychopathology: Evidence of moderating and mediating effects. *Clinical Psychology Review, 26*, 257–283. https://doi.org/10.1016/j.cpr.2005.06.011

Grych, J., Taylor, E., Banyard, V., & Hamby, S. (2020). Applying the dual factor model of mental health to understanding protective factors in adolescence. *American Journal of Orthopsychiatry, 9*(4), 458–467. https://doi.org/10.1037/ort0000449

Gunderson, E. A., Gripshover, S. J., Romero, C., Dweck, C. S., Goldin-Meadow, S., & Levine, S. C. (2013). Parent praise to 1-to 3-year-olds predicts children's motivational frameworks 5 years later. *Child Development, 84*(5), 1526–1541.

Held, M. L., Jones, A., & Forrest-Bank, S. (2020). Predictors of Latinx youth health and emotional well-being: Social determinants of health perspective. *Journal of Racial and Ethnic Disparities, 7*, 1188–1201. https://doi.org/10.1007/s40615-020-00744-4

Herman, K. C., Cohen, D., Reinke, W. M., Ostrander, R., Burrell, L., McFarlane, E., & Duggan, A. K. (2018). Using latent profile and

transition analyses to understand patterns of informant ratings of child depressive symptoms. *Journal of School Psychology, 69*, 84–99. https://doi.org/10.1016/j.jsp.2018.05.004

Kern, M. L., Waters, L. E., Adler, A., & White, M. A. (2015). A multidimensional approach to measuring well-being in students: Application of the PERMA framework. *The Journal of Positive Psychology, 10*(3), 262–271. https://doi.org/10.1080/17439760.2014.936962

Kim, E. K., Dowdy, E., Furlong, M. J., & You, S. (2017). Mental health profiles and quality of life among Korean adolescents. *School Psychology International, 38*, 98–116. https://doi.org/10.1177/0143034316682296

Lam, K. K. L. (2020). The mediating effect of gratitude in the relationship between zest for life and depression. *Personality and Individual Differences, 171*, 110476. https://doi.org/10.1016/j.paid.2020.110476

Lanza, S. T., Tan, X., & Bray, B. C. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural Equation Modeling: A Multidisciplinary Journal, 20*(1), 1–26. https://doi.org/10.1080/10705511.2013.742377

Lenzi, M., Dougherty, D., Furlong, M. J., Sharkey, J., & Dowdy, E. (2015a). The configuration protective model: Factors associated with adolescent behavior and emotional problems. *Journal of Applied Developmental Psychology, 38*, 49–59. https://doi.org/10.1016/j.appdev.2015.03.003

Lenzi, M., Furlong, M. J., Dowdy, E., Sharkey, J., Gini, G., & Altoè, G. (2015b). The quantity and variety across domains of psychological and social assets associated with school victimization. *Psychology of Violence, 5*(4), 411–421. https://doi.org/10.1037/a0039696

Leonard, J. A., Garcia, A., & Schulz, L. E. (2020). How adults' actions, outcomes, and testimony affect preschoolers' persistence. *Child Development, 91*(4), 1254–1271. https://doi.org/10.1111/cdev.13305

Leonard, J. A., Martinez, D. N., Dashineau, S. C., Park, A. T., & Mackey, A. P. (2021). Children persist less when adults take over. *Child Development, 92*, 1325–1336. https://doi.org/10.1111/cdev.13492

Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika, 88*(3), 767–778. https://doi.org/10.1093/biomet/88.3.767

Mahdiani, H., & Ungar, M. (2021). The dark side of resilience. *Adversity and Resilience Science, 2*(3), 147–155. https://doi.org/10.1007/s42844-021-00031-z

Masyn, K. E. (2013). Latent class analysis and finite mixture modeling. In T. D. Little (Ed.), *The Oxford handbook of quantitative methods* (Vol. 2: Statistical analysis, pp. 551–611). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199934898.013.0025

McLachlan, G. J., & Peel, D. (2000). Finite mixture models. *Wiley*. https://doi.org/10.1002/0471721182

McNeely, C. A., Nonnemaker, J. M., & Blum, R. W. (2002). Promoting school connectedness: Evidence from the national longitudinal study of adolescent health. *Journal of School Health, 72*(4), 138–146. https://doi.org/10.1111/j.1746-1561.2002.tb06533.x

McPherson, C. M., & McGibbon, E. A. (2010). Addressing the determinants of child mental health: Intersectionality as a guide to primary health care renewal. *Canadian Journal of Nursing Research, 42*(3), 50–64.

Meyer, I. H. (2013). Prejudice, social stress, and mental health in lesbian, gay, and bisexual populations: Conceptual issues and research evidence. *Psychology of Sexual Orientation and Gender Diversity, 1*(S), 3–26. https://doi.org/10.1037/2329-0382.1.S.3

Miele, D. B., Browman, A. S., Chen, S., Vasilyeva, M., & Tyumeneva, Y. A. (2020). Domain-general and math-specific self-perceptions of perseverance as predictors of behavioral math persistence. *The Journal of Experimental Education, 90*(3), 593–614. https://doi.org/10.1007/s11482-016-9464-9

Miller, R. B., Greene, B. A., Montalvo, G. P., Ravindran, B., & Nichols, J. D. (1996). Engagement in academic work: The role of learning goals, future consequences, pleasing others, and perceived ability. *Contemporary Educational Psychology, 21*, 388–422. https://doi.org/10.1006/ceps.1996.0028

Moore, S. A., Dowdy, E., Nylund-Gibson, K., & Furlong, M. J. (2019a). An empirical approach to complete mental health classification in adolescents. *School Mental Health, 11*, 438–453. https://doi.org/10.1007/s12310-019-09311-7

Moore, S. A., Dowdy, E., Nylund-Gibson, K., & Furlong, M. J. (2019b). A latent transition analysis of the longitudinal stability of dual-factor mental health in adolescence. *Journal of School Psychology, 73*, 56–73. https://doi.org/10.1016/j.jsp.2019.03.003

Moore, S. A., Long, A. C., Coyle, S., Cooper, J. M., Mayworm, A. M., Amirazizi, S., Edyburn, K. L., Pannozzo, P., Choe, D., Miller, F. G., Eklund, K., Bohnenkamp, J., Whitcomb, S., Raines, T. C., & Dowdy, E. (2023). A roadmap to equitable school mental health screening. *Journal of School Psychology, 96*, 57–74. https://doi.org/10.1016/j.jsp.2022.11.001

Moore, S. A., Widales-Benitez, O., Carnazzo, K. W., Kim, E. K., Moffa, K., & Dowdy, E. (2015). Conducting universal complete mental health screening via student self-report. *Contemporary School Psychology, 19*(4), 253–267. https://doi.org/10.1007/s40688-015-0062-x

Muthén, B. (2003). Statistical and substantive checking in growth mixture modeling: Comment on Bauer and Curran (2003). *Psychological Methods, 8*(3), 369–377. https://doi.org/10.1037/1082-989x.8.3.369

Muthén, L. K., & Muthén, B. O. (1998–2017). *Mplus user's guide*. Eighth edition. Muthén & Muthén. https://www.statmodel.com/download/usersguide/MplusUserGuideVer_8.pdf

National Council of La Raza. (2016). *Toward a more equitable future: The trends and challenges facing America's Latino children*. https://bit.ly/3MM5fBF

Ng, Z. J. (2019). *Emotion regulation and life satisfaction of early adolescents in the face of stressful life events* (Order No. AAI10638175). Available from APA PsycInfo®. (2169374702; 2018-65234-068). Retrieved from https://bit.ly/47eTY5a

Ng, Z. J., Huebner, E. S., Maydeu-Olivares, A., & Hills, K. J. (2018). Confirmatory factor analytic structure and measurement invariance of the Brief Multidimensional Students' Life Satisfaction Scale (BMSLSS) in a longitudinal sample of adolescents. *Child Indicators Research, 11*(4), 1237–1247. https://doi.org/10.1007/s12187-017-9468-5

Nickerson, A. B., & Fishman, C. E. (2013). Promoting mental health and resilience through strength-based assessment in US schools. *Educational & Child Psychology, 30*(4), 7–17. https://doi.org/10.53841/bpsecp.2013.30.4.7

Nylund-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science, 4*(4), 440. https://doi.org/10.1037/tps0000176

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

Nylund-Gibson, K., & Masyn, K. E. (2016). Covariates and mixture modeling: Results of a simulation study exploring the impact of misspecified effects on class enumeration. *Structural Equation Modeling, 23*(6), 782–797. https://doi.org/10.1080/10705511.2016.122131

Petersen, A. C., Kennedy, R. E., & Sulivan. (1991). Coping with adolescence. In M. E. Colten & S. Gore (Eds.), *Adolescent stress: Causes and consequences* (pp. 93–110). Aldine de Gruyter.

Petersen, K. J., Humphrey, N., & Qualter, P. (2020). Latent class analysis of mental health in middle childhood: Evidence for the dual-factor model. *School Mental Health, 12*, 786–800. https://doi.org/10.1007/s12310-020-09384-9

Petersen, K. J., Qualter, P., & Humphrey, N. (2019). The application of latent class analysis for investigating population child mental health: A systematic review. *Frontiers in Psychology, 10*, 1214. https://doi.org/10.3389/fpsyg.2019.01214

Piqueras, J. A., Rodriguez-Jiminez, T., Marzo, J. C., Rivera-Riquelme, M., Martinez-Gonzalez, A. E., Falco, R., & Furlong, M. J. (2019). Social emotional health survey-secondary (SEHS-S): A universal screening measure of social-emotional strengths for Spanish-speaking adolescents. *International Journal of Environmental Research and Public Health, 16*(24), 4982. https://doi.org/10.3390/ijerph16244982

Priest, N., Paradies, Y., Trenerry, B., Truong, M., Karlsen, S., & Kelly, Y. (2013). A systematic review of studies examining the relationship between reported racism and health and wellbeing for children and young people. *Social Science & Medicine, 95*, 115–127. https://doi.org/10.1016/j.socscimed.2012.11.031

Rebelez-Ernst, J. L. (2015*). Capturing complete mental health among adolescents: Investigation of covitality latent class typologies.* Doctoral Dissertation, University of California, Santa Barbara. https://www.proquest.com/docview/1735793402

Reiss, F. (2013). Socioeconomic inequalities and mental health problems in children and adolescents: A systematic review. *Social Science & Medicine.* https://doi.org/10.1016/j.socscimed.2013.04.026

Renshaw, T. L., Furlong, M. J., Dowdy, E., Rebelez, J., Smith, D. C., O'Malley, M. D., Lee, S.-Y., & Strøm, I. F. (2014). Covitality: A synergistic conception of adolescents' mental health. In M. J. Furlong, R. Gilman, & E. S. Huebner (Eds.), *Handbook of positive psychology in schools* (2nd ed., pp. 12–32). Berlin: Routledge/Taylor & Francis.

Renshaw, T. L., Long, A. C. J., & Cook, C. R. (2015). Assessing adolescents' positive psychological functioning at school: Development and validation of the student subjective wellbeing questionnaire. *School Psychology Quarterly, 30*(4), 534–552. https://doi.org/10.1037/spq0000088

Romer, N., Ravitch, K., Tom, K., & Merrell, K. W. (2011). Gender differences in positive social-emotional functioning. *Psychology in the Schools, 48*(10), 958–970. https://doi.org/10.1002/pits.20604

Ross, K. M., & Tolan, P. (2018). Social and emotional learning in adolescence: Testing the CASEL model in a normative sample. *The Journal of Early Adolescence, 38*(8), 1170–1199. https://doi.org/10.1177/0272431617725198

Roth, R. A., Suldo, S. M., & Ferron, J. M. (2017). Improving middle school students' subjective well-being: Efficacy of a multicomponent positive psychology intervention targeting small groups of youth. *School Psychology Review, 46*(1), 21–41. https://doi.org/10.1080/02796015.2017.12087610

Rubin, D. B. (1987). Multiple imputation for Nonresponse in surveys. *Wiley.* https://doi.org/10.1002/9780470316696

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics, 6*(2), 461–464.

Sclove, S. L. (1987). Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika, 52*(3), 333–343. https://doi.org/10.1007/bf02294360

Seligman, M., & Csikszentmihalyi, M. (2000). Positive psychology: An introduction. *American Psychologist, 55*(1), 5–14. https://doi.org/10.1037/0003-066X.55.1.5

Solar, O., & Irwin, A. (2010). *A conceptual framework for action on the social determinants of health. Social Determinants of Health Discussion Paper 2 (Policy and Practice).* World Health Organization. https://www.who.int/publications/i/item/9789241500852

Suldo, S. M. (2016). *Promoting student happiness: Positive psychology interventions in schools.* The Guilford Press.

Suldo, S. M., & Shaffer, E. J. (2008). Looking beyond psychopathology: The dual-factor model of mental health in youth. *School Psychology Review, 37*, 52–68. https://doi.org/10.1080/02796015.2008.12087908

Suldo, S. M., Savage, J. A., & Mercer, S. H. (2014). Increasing middle school students' life satisfaction: Efficacy of a positive psychology group intervention. *Journal of Happiness Studies, 15*, 19–42. https://doi.org/10.1007/s10902-013-9414-2

Suldo, S. M., Thalji-Raitano, A., Kiefer, S. M., & Ferron, J. M. (2016). Conceptualizing high school students' mental health through a dual-factor model. *School Psychology Review, 45*(4), 434–457. https://doi.org/10.17105/SPR45-4

Tangney, J. P., Baumeister, R. F., & Boone, A. L. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *Journal of Personality, 72*(2), 271–322. https://doi.org/10.1111/j.0022-3506.2004.00263.x

Telef, B., & Furlong, M. J. (2017). Social and emotional psychological factors associated with subjective well-being: A comparison of Turkish and California adolescents. *Cross-Cultural Research: THe Journal of Comparative Social Science, 51*(5), 491–520. https://doi.org/10.1177/1069397117694815

Travis, R., Jr., & Leech, T. G. J. (2013). Empowerment-based positive youth development: A new understanding of healthy development for African American youth. *Journal of Research on Adolescence, 24*(1), 93–116. https://doi.org/10.1111/jora.12062

Usher, E. L., Li, C. R., Butz, A. R., & Rojas, J. P. (2019). Perseverant grit and self-efficacy: Are both essential for children's academic success? *Journal of Educational Psychology, 111*(5), 877–902. https://doi.org/10.1037/edu0000324

Vermunt, J. K. (2004). Latent profile model. In M. S. Lewis-Beck, A. Bryman, & T. F. Liao (Eds.), *The Sage encyclopedia of social sciences research methods* (pp. 554–555). Sage.

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis, 18*(4), 450–469.

Viner, R. M., Ozer, E. M., Denny, S., Marmot, M., Resnick, M., Fatusi, A., & Currie, C. (2012). Adolescence and the social determinants of health. *The Lancet, 379*(9826), 1641–1652. https://doi.org/10.1016/S0140-6736(12)60149-4

World Health Organization. (2016). *Mental health: Strengthening our response* (Fact Sheet). https://bit.ly/3SGw3XF

You, S., Furlong, M. J., Felix, E., & O'Malley, M. (2015). Validation of the Social and Emotional Health Survey for five sociocultural groups: Multigroup invariance and latent mean analyses. *Psychology in the Schools, 52*(4), 349–362. https://doi.org/10.1002/pits.21828

Zhang, W., Li, H., Gong, Y., & Ungar, M. (2013). Stressful events and depression among Chinese adolescents: The mitigating role of protective factors. *School Psychology International, 34*(5), 501–513. https://doi.org/10.1177/0143034312472760

Zhen, R., Liu, R., Ding, Y., Jiang, R., Jiang, S., & Hong, W. (2021). Gratitude and academic engagement among primary students: Examining a multiple mediating model. *Current Psychology: A Journal for Diverse Perspectives on Diverse Psychological Issues, 40*(5), 2543–2551. https://doi.org/10.1007/s12144-019-00202-3