Towards an Enhanced Understanding of the Dual Factor Model of Mental Health

Pre-Publication Copy

Furlong, M. J., Chan, M-K., Dowdy, E., Park, H-K., Nylund-Gibson, K, & Geng, A. (2025). Toward an Enhanced Understanding of the Dual-Factor Model of Mental Health. *School Mental Health*. https://doi.org/10.1007/s12310-025-09816-4

Michael J. Furlong [1], Mei-ki Chan [2], Erin Dowdy [1], Hee-Kyung Park [1], Karen Nylund-Gibson [3] Alicia Geng [1]

1 School Mental Health Collaborative, University of California Santa Barbara, Santa Barbara, CA, USA

2 Department of Psychology, University of California, Berkeley, CA, USA

3 Department of Education, University of California, Santa Barbara, CA, USA

Corresponding Author: Michael Furlong, email: mfurlong@ucsb.edu

Postal Address: University of California Santa Barbara, Department of Counseling, Clinical, and School Psychology, Santa Barbara, CA 93016, USA

ORCIDs

Michael J. Furlong https://orcid.org/0000-0001-5011-4565

Mei-ki Chan https://orcid.org/0000-0001-6451-2417

Erin Dowdy https://orcid.org/0000-0001-6402-3277

Hee-Kyung Park https://orcid.org/0009-0006-6318-4793

Karen Nylund-Gibson https://orcid.org/0000-0003-3499-1052

Credit Author Statement

Michael J. Furlong: Conceptualization, Resources, Writing: Original draft preparation, Writing: Reviewing and editing **Mei-ki Chan:** Conceptualization, Methodology, Data Curation, Formal analysis, Writing: Original draft preparation, Writing: Reviewing and editing, Visualization. **Erin Dowdy:** Conceptualization, Funding Acquisition, Resources, Writing: Original draft preparation, Writing: Reviewing and editing. **Hee-Kyung Park:** Conceptualization, Writing: Original draft preparation, Writing: Reviewing and editing. **Michael J. Furlong:** Conceptualization, Resources, Writing: Original draft preparation, Writing: Reviewing and editing. **Karen Nylund-Gibson:** Methodology, Writing: Reviewing and editing **Alicia Geng**, Resources, Writing, Reviewing

Declaration of Conflicts, Funding, and Data Accessibility

The authors have no competing interests to declare that are relevant to the content of this article.

No funding was received to assist with the preparation of this manuscript.

The datasets generated by the survey research during and/or analyzed during the current study are from the 2023/2024 California Healthy Kids Survey, available from WestEd, https://calschls.org/about/the-surveys/#chks

Abstract

Various studies and methodological approaches have been used to examine indicators of distress and wellness aligned with a dual factor model (DFM) of mental health. Through a review of the DFM literature and this study's analyses, this paper aims to gain a deeper understanding of DFM and enhance its value as a resource for research and practical implementation in schools. Latent Profile Analysis (LPA) techniques were applied and replicated using two large population size samples (Sample A: n = 17,358; Sample B: n = 17,927), randomly drawn from a larger sample of 538,527 California adolescents in grades 6-12. The LPA used the California Student Wellness Index (CSWI), which was developed, co-normed, and intended for use within the DFM framework. Three ordered latent profiles were identified (i.e., Flourishing, Moderate, and Troubled) with expected associations with distal outcomes of depressed and hopeless mood, suicidal thoughts, school connectedness, academic grades, and school absences. Results highlight how classic DFM groupings are the products of the algorithms used to create them and are not consistently replicated through empirical methods. The need for standardized approaches for DFM research and practice is discussed.

Keywords: dual-factor model, school mental health, screening, school, LPA, wellness index

Towards an Enhanced Understanding of the Dual Factor Model of Mental Health

The youth mental health crisis has reached concerning levels in recent years, particularly in the aftermath of the COVID-19 pandemic, underscoring the urgent need for a more comprehensive approach and understanding of mental health in youth (Kieling et al., 2011; Zhang-James et al., 2025). In 2021, the USA Centers for Disease Control and Prevention reported that over 40% of high school students experienced persistent feelings of sadness or hopelessness, and nearly 20% seriously considered suicide (Centers for Disease Control and Prevention, 2022). These statistics highlight the level of distress among youth, which has been shown to have long-term, detrimental academic, social, and health effects (Kenny et al., 2013; Rai et al., 2012; Shonkoff et al., 2012). Adolescence is also a critical developmental window during which mental health trajectories are shaped, meaning early identification and intervention efforts can yield significant benefits over the life course (Sisk & Gee, 2022). Continued efforts and focus on improving youth mental health and wellbeing are a necessary and proactive investment in the resilience of the next generation.

Since young people spend most of their time in educational settings, schools play a critical role in identifying and addressing the mental health needs of adolescents. (Hoover & Bostic, 2021). A growing body of research has shown the need for comprehensive mental health screening of students to provide school-based mental health services effectively (Zabek et al., 2023). Universal mental health screening practices, administered proactively across student populations, allow schools to move beyond reactive models of care and toward data-driven prevention and early intervention (Dowdy et al., 2010). Universal mental health screening can enhance equity in care access and reinforce a culture of mental health promotion, fostering safer and more nurturing learning environments for all students.

To fully capitalize on the potential of school-based screening, it is essential to shift from a sole focus on the absence of psychopathology to a more complete conceptualization of mental health. The Dual Factor Model (DFM) of mental health posits that psychological functioning is characterized by two primary dimensions or continua: psychopathology and subjective well-being (SWB) (Greenspoon & Saklofske, 2001; Keyes, 2006). Comprehensive, complete mental health screening should assess both dimensions to identify students struggling emotionally, even in the absence of clinical pathology, as well as those who appear outwardly successful but are at risk of their mental health deteriorating (Moore et al., 2019). Utilizing a DFM lens facilitates schools in delivering individualized support that addresses distress and promotes flourishing and overall positive development. However, to implement screening and subsequent support within a DFM approach, it is crucial to fully understand the intentions, subsequent adaptations, and methodological limitations of the DFM mental health research. This study aims to provide an enhanced understanding of the DFM through a critical analysis of research and an examination of one measure, the California Student Wellness Index (CSWI), which was developed with the explicit intention of school-based screening within a DFM framework.

Reconceptualizing Youth Mental Health: Foundational Considerations

Greenspoon and Saklofske (2001) introduced the term "dual-factor system" of mental health, challenging traditional, unidimensional perspectives that equate low psychopathology with positive mental health. Historically, mental health has been viewed as a unidimensional continuum, with a high number of symptoms indicating low mental health on one end and high subjective well-being on the other. However, in their groundbreaking study, they explored a group of students exhibiting low levels of psychopathology but also reporting diminished subjective well-being (SWB)—initially labeled as "dissatisfied" and referred to as "vulnerable" in later research. Students with this unique "vulnerable" profile do not fulfill the criteria for a diagnosable disorder, yet they remain at risk for experiencing suboptimal well-being. Furthermore, Greenspoon and Saklofske (2001) sought to identify the characteristics of another group of youths who displayed externalizing behavior problems while reporting high levels of subjective well-being. These individuals, characterized as "externally maladjusted," may be most effectively understood within the context of psychopathy, further emphasizing the complexity of youth mental health.

In their initial study, Greenspoon and Saklofske (2001) focused on a sample of fourth- and fifth-grade students. The participants completed a 341-item survey across two sessions lasting 150 minutes. Subjective well-being was evaluated using the 40-item Multidimensional Student Life Satisfaction Scale (MSLSS; Huebner, 1994). Internalizing pathology was assessed through the Behavior Assessment System for Children Self-Report of Personality (BASC SRP; Reynolds & Kamphaus, 1992), whereas externalizing pathology was measured using the BASC Teacher Rating Scales (TRS; Reynolds & Kamphaus, 1992). The students' subjective well-being values were determined based on their rank order within the sample distribution. BASC values were represented as *T*-scores adjusted for age norms (see Supplemental Information (SI) Table SI 1).

Greenspoon and Saklofske (2001) used the percentile cut-point method to categorize students into four distinct groups based on low/high subjective well-being (SWB) and psychopathology (PATH) scores.

- Group 1 (Well-Adjusted) included students with high SWB and low PATH levels.
- Group 2 (Distressed) had low SWB and high PATH.
- Group 3 (Dissatisfied) had low SWB but low PATH.

- Group 4 (Externally Maladjusted) displayed high SWB and high PATH.

Subsequent research often labeled these groups as follows: Group 1 as having Complete Mental Health (CMH), Group 2 as Troubled, Group 3 as Vulnerable, and Group 4 as Symptomatic but Content (SBC).

Although later research on what would be called the Dual-Factor Model (DFM) simultaneously examined and compared all four dual-factor groups in their analyses, Greenspoon and Saklofske (2001) conducted two discriminant function analyses that did not include all four groups simultaneously. Both of their analyses included Group 1 (well-adjusted; CMH) and Group 2 (distressed; troubled), and in separate analyses, they compared these groups to either Group 3 (dissatisfied; vulnerable) or Group 4 (externally maladjusted; symptomatic but content). It is important to note that the criteria used to designate cut-points for low and high levels of SWB and pathology varied for each analysis. In the study based on internalizing self-reports, the bottom 40% of the sample was defined as having low SWB and pathology. In comparison, the top 40% were classified as having high SWB and pathology. Greenspoon and Saklofske (2001) excluded the middle 20% of the sample from this analysis. In the analysis involving teacher reports of externalizing behavior problems, low SWB — high pathology was defined as the bottom 35% of the sample, and the top 35% were classified as high SWB and low pathology. The authors excluded the middle 30% to enhance group differentiation. They excluded the middle 20% and 35% of the sample to "increase the probability of uncovering group differences" (Greenspoon & Saklofske, 2001, p. 87).

Using discriminant function analyses, Greenspoon and Saklofske (2001) argued that their exploratory study justified examining cross-group differences for 23 predictor variables (e.g., self-concept, social stress, interpersonal relations). They entered eight predictors for the first analysis, comparing Group 3 (dissatisfied; vulnerable) and six predictors for the analysis of Group 4 (externally maladjusted; SBC). Although only some of their empirical findings reached statistical significance, the lasting impact of their work lies in their advocacy for examining the multifaceted nature of youth mental health. Beyond the expanded conceptualization of youth mental health, perhaps their most influential contribution was introducing a cut-point method for categorizing dual-factor groups based on subjective well-being and mental health symptoms. This methodology has since been widely adopted by researchers investigating psychological indicators of mental health in young individuals.

DFM Research: Cut-Point Approach for Group Formation

Building upon the foundational work of Greenspoon and Saklofske (2001), Suldo and Shaffer (2008) adapted their methodology to examine the dual-factor model of mental health further. This topic is particularly pertinent to school practices founded on positive psychology principles (Seligman et al., 2009) and positive education (Waters & Loton, 2019). Their dual-factor model (DFM) emphasizes the necessity of a balanced understanding of mental health, considering the perspectives of school-aged children from its inception.

Suldo and Shaffer (2008) expanded on the work of Greenspoon and Saklofske (2001) by developing an integrated DFM that simultaneously identified four prototypical groups (see Table SI 2). Their subjective well-being (SWB) index included two components: the wellness factor from the Student Life Satisfaction Scale (SLSS; Huebner, 1991) and the Positive and Negative Affect Scale (PANAS; Laurent et al., 1999). A composite SWB score was calculated using sample-specific *z*-scores from these scales. Psychopathology was assessed using the Achenbach Child Behavior Checklist scale, with the Child Self-Report assessing for internalizing symptoms and the Teacher Report assessing for externalizing symptoms (Achenbach & Rescorla, 2001). Students with *T* scores of 60 or higher on either measure were considered to have high symptoms, identifying approximately 30% of students as symptom-positive. To define SWB categories, students in the bottom 30% of the distribution were classified as having low SWB, while all others were considered to have average or high SWB. Unlike earlier models, Suldo and Shaffer (2008) assigned different labels to the four resulting groups: *Complete Mental Health* (high SWB, low symptoms), *Vulnerable* (low SWB, low symptoms), *Symptomatic but Content* (high SWB, high symptoms), and *Troubled* (low SWB, high symptoms).

Research Expanding upon the Validity of the DFM Framework

Building on the analysis by Suldo and Shaffer (2008), a substantial body of research (see Table SI 2) further explored the DFM (e.g., Antaramian et al., 2010; Grych et al., 2020; Kelly et al., 2012; Lyons et al., 2012; Zhou et al., 2020). These studies enhanced the proof of concept for considering both psychological symptoms and indicators of wellness, providing researchers and practitioners with a more comprehensive understanding of youth psychosocial development. Specifically, the research identified differences among DFM groups across various developmental stages, including children (Smith et al., 2020), adolescents in middle school (Antaramian et al., 2010) and high school (Suldo et al., 2016), as well as adults (Renshaw & Cohen, 2014). Individuals with high well-being and low psychopathology, representing complete mental health, experience the most favorable outcomes. Individuals with *Complete Mental Health*—those with high well-being and low psychopathology—consistently demonstrated the most favorable outcomes. These include higher academic achievement (Antaramian et al., 2010; Lyons et al., 2012), greater engagement (Antaramian et al., 2010; Lyons et al., 2012; Smith et al., 2020), stronger social skills (Suldo et al., 2016), better physical health (Suldo & Shaffer, 2008; Suldo et al., 2016), more positive identity development (Suldo et al., 2016), and greater perceived social support (Smith et al., 2020).

The fact that youth with complete mental health have better outcomes compared to those who are more vulnerable highlights that simply being free of psychopathology is not enough to nurture optimal developmental outcomes (Antaramian et al., 2010). Moreover, research indicates that well-being can be protective when students are experiencing psychological distress. Adolescents who exhibit symptoms of psychological distress along with indicators of wellness are likely to manifest more favorable outcomes compared to those with psychological symptoms and few indicators of wellness (Grych et al., 2020; Lyons et al., 2012; Suldo et al., 2016; Smith et al., 2020). Overall, these various studies on the DFM demonstrate significant differences in outcomes between groups that display similar levels of psychopathology but differ in their levels of subjective well-being. Additionally, the prototypical groups defined by the DFM—complete mental health and troubled groups—show considerable differences across numerous quality-of-life indicators. A robust body of research supports the core DFM principle: optimal assessment of youth mental health should simultaneously consider indicators of distress and dimensions of wellness (Iasiello & Van Agteren, 2020).

Latent Profile Analysis and Empirical DFM Group Identification

The initial phase of DFM introduced by Suldo and Shaffer (2008) was followed by a series of replication studies (Antaramian et al., 2010; DiLeo et al., 2022; Kelly et al., 2012; Lyons et al., 2012) and other studies (González et al., 2023; Grych et al., 2020; Hermann et al., 2024; Jefferies et al., 2023; King et al., 2021; Renshaw et al., 2024; Xiong et al., 2017; see Table SI 3) that used the same general cut-point method to form the four DFM groups with some variations in measures to explore different wellbeing and distress measures across diverse populations. Researchers began to reevaluate the interpretation of cut-point values, noting the absence of a standardized approach and a clear rationale for their application. In response, some studies started employing Latent Profile Analysis (LPA) as an empirically driven method to identify DFM groups, which, it was argued, allows the data to guide the findings and reveal common underlying DFM patterns. LPA-based studies aimed to determine the optimal number and nature of mental health profiles based on underlying patterns in the data without relying on arbitrary categorizations based on distinct cut points (Petersen et al., 2019).

A growing number of studies (see Table SI 4) have since applied LPA to empirically identify mental health subgroups within the Dual-Factor Model (DFM) framework across multiple age groups and cultural contexts (Clark & Malecki, 2022; Clark et al., 2024; Gregory et al., 2024; Jiang et al., 2023; Maurer et al., 2025; Moore et al., 2019; Wang et al., 2025; Zhang et al., 2025; Zhou et al., 2020). In addition to identifying classes and understanding the profiles of each group, some longitudinal studies examined the transitions of mental health profiles over time. LPA research typically identified three to six profiles across studies.

While many studies have revealed patterns resembling the traditional DFM groups—Complete Mental Health, Vulnerable, Troubled, and Symptomatic but Content—others have identified hybrid or mid-range profiles, such as “moderate mental health,” “symptomatic but managing,” or “content but symptomatic.” For instance, Zhou et al. (2020), Clark and Malecki (2022), and Zhang et al. (2025) identified three classes of mental health. While these three studies identified the CMH and Troubled group, there were variations in identifying the middle SBC and Vulnerable groups. Zhou et al. (2020) found a Vulnerable group but not an SBC group. On the other hand, Clark and Malecki (2022) identified an SBC but not a Vulnerable group. Zhang et al. (2025) identified three groups: Moderate Mental Health, CMH, and Troubled. In addition to studies identifying three classes, Gregory et al. (2024) found five classes, which include CMH, SBC, Troubled, and two unique LPA classes labeled Good Mental Health and Moderate Mental Health. Sechague Monroy et al. (2024) also identified six classes, in addition to the four classic DFM groups, including Moderate Troubled and Moderate Mental Health.

While LPA approaches allow for the identification of different groups of students with similar patterns, the number and characteristics of these groups have varied significantly across these studies. There may be various reasons for the inconsistencies including differences in the sample sizes (ranging from 365 to 75,757); various dimensions, measures, and indicators of wellness (e.g., Brief Multidimensional Life Satisfaction Scale, Student Life Satisfaction Scale, Positive and Negative Affect Scale, Social Emotional Health Survey, EPOCH Measurement of Adolescent Wellbeing, Mental Health Continuum-Short Form); and various dimensions, measures, and indicators of distress or psychopathology (e.g., Strengths & Difficulties Questionnaire, Depression Self-Rating Scale, Youth Self-Report Form, Depression Anxiety Stress Scale-21, Aggression Questionnaire, Negative Affect Scale, Patient Health Questionnaire-4, Seattle Personality Questionnaire). In addition, as Table SI 2 shows, various studies employed different approaches to analyze the indicators, including *z*-scores and raw scores.

The exploration of dual factor mental health through research studies has garnered significant attention, particularly concerning the prevalence of symptoms and the effectiveness of support systems. However, the current DFM body of research is fraught with limitations and needs additional research to enhance the understanding of youth mental health. A principal concern with the cut-score approach to DFM is the reliance on specific cut points used in analyses, where the absence of a standardized method for their determination raises questions about the validity of the findings. The identification of four distinct groups in these studies is heavily contingent upon the measures employed, resulting in difficulties when comparing outcomes across different studies due to variability in both cut points and the inherent characteristics of the tools used. Limitations in the LPA approach are also present, with varying samples and different measures being used, leading to inconsistencies in the number and characteristics of student mental health profiles. In summary, while the current studies have advanced our understanding, they also underscore the need for more standardized and comprehensive approaches to DFM research.

Promising Measure for DFM Research and Practice: California Student Wellness Index

The CSWI (Furlong et al., 2024) was developed as a co-normed assessment tool to address some of the DFM's limitations and the pressing need for standardization. This tool evaluates subjective well-being and monitors emotional distress, filling gaps in current methodologies. The CSWI provides a composite index based on 10 items, including two fundamental dimensions of wellness: student self-reported life satisfaction and social-emotional distress. This index scores range from 0 to 40 and serve as an indicator of optimal mental health. Higher scores reflect lower levels of distress and greater life satisfaction. It can be used both as an aggregate measure for analyzing trends in mental health at the school district and state levels, as well as an individual score to assess student well-being. The strength of the CSWI lies in its development, conceptualization, and validation within the DFM framework, which systematically examines the distributions of distress and wellness in a co-normed context.

While succinct with just ten items, the CWSI demonstrates significant validity in evaluating students' social-emotional health. Research has highlighted a robust correlation between the CSWI and critical risk indicators of chronic sadness and severe suicidal ideation; a Receiver Operating Characteristic (ROC) analysis revealed that the total CSWI score attained an area under the curve value of 0.86 (Furlong et al., 2024). Furthermore, the CWSI exhibits substantial stability over a one-year period, with a correlation of $r_{\text{t1-t2}} = .61$. It also demonstrates strong concurrent and predictive validity compared to other established well-being assessments. Notably, it correlates significantly with psychological well-being, as measured by the Mental Health Continuum-Short Form, with concurrent correlations of $r = .61$ and one-year predictive validity of $r = .48$ (Furlong et al., 2024). These findings highlight the CWSI's promising potential for universal wellness screening to identify and support students with social-emotional needs.

The CSWI was chosen for this study as it is the first known tool designed and explicitly co-normed for use in DFM research and practice. Its integration of co-normed distress and wellness items makes it especially useful for identifying nuanced student mental health profiles and monitoring trends over time. It is routinely administered to large population-based samples, making it a robust and scalable tool to inform DFM research and school-based mental health practice.

Study Purpose

The DFM has made valuable contributions and significantly enhanced the field's understanding of mental health, including multiple dimensions of wellness and distress. However, the DFM has several key limitations, diminishing its ability to advance research and practical applications. In particular, DFM research has relied on sample-specific methods that are not easily replicable; there is no standard for simultaneously measuring its components and no consensus on cut points for categorizing groups. Additionally, the joint distribution of co-normed wellness and distress factors has not been studied, as the measures employed in DFM studies were not designed and validated for co-administration within the DFM framework. Furthermore, the measures used in DFM research often have too many items for practical universal screening of youth mental health. These limitations widen the gap between research and practical applications (Furlong et al., 2024), making it challenging for school mental health professionals to effectively utilize DFM measures and applications in schools. In short, the DFM model has not been adequately validated for use in real-world schoolwide wellness screenings.

Given the limitations of the DFM cut-score approaches, methodological advancements using LPA have been applied. However, overall, LPA has produced inconsistent findings regarding the number of profile classes and has not generally reproduced the four classic DFM groups examined in cut-point studies. One reason for this is that the studies continued to use varying measures, none of which were designed explicitly with the DFM model in mind. Additionally, the sample sizes and characteristics varied, limiting the ability to comprehensively examine the mental health profiles in a large population-based sample of adolescents. Furthermore, LPA is not designed to create four distinct DFM groups based on cut scores; therefore, even if a similar number of groups or LPA profiles is found, the nature and composition of the membership in those groups will differ. As such, the number and distinctiveness of standard DFM classes among school-age youths remain unclear regardless of whether a cut-score or LPA approach is applied.

In response to these noted gaps in the DFM literature, this study aimed to (a) examine youth mental health profiles using a measure (i.e., the California Student Wellness Index) that was specifically developed, validated, and intended for use within a DFM framework and (b) applied LPA to this measure using a large population sample to evaluate the number and characteristics of DFM groups in a general population of students. We recognize that a single study cannot substantiate the "true" number of profiles or groups utilizing a DFM framework, and we also acknowledge the need for continued scrutiny and examination of studies to gain a deeper understanding of youth mental health and how to apply this understanding to inform school-based screening efforts. As such, this study aims to deepen knowledge of DFM and enhance its value as a resource for research and practical implementation in school settings. We present an in-depth examination of the CSWI and recognize the need for continued critiques and advancements in DFM research.

Method

Participants and Procedure

The California Healthy Kids Survey (CHKS) was the data source for the present study. The CHKS is a statewide survey that collects anonymous information regarding student risk behaviors and resilience factors, including the CSWI, with participation from students in 56 of the state's 58 counties. The survey administration was standardized, with trained school personnel using a script to reassure students that their responses would remain anonymous and that participation was voluntary. Students provided assent and then completed the survey during school hours. Parents granted passive consent according to established procedures (see http://chks.wested.org/administer/instructions). The Human Subjects Committee at the authors' university has determined that ethical approval is waived for this study. The students included in this study passed response quality checks based on inconsistent response patterns and inflated reports of the frequency of substance use.

We included student responses from the 2023/24 academic year who received in-person instruction and successfully passed quality checks related to their substance use and honesty responses. As a result, 3.31% of the students were removed from the study, leaving a final sample size of 538,527 students.

For the data analysis in this study, we utilized two randomly selected subsamples: Sample A (N = 17,358) and Sample B (N = 17,927). While the two samples were comparable in demographic characteristics, they differed in aspects such as racial and ethnic identity, gender, sexual orientation, and family background. Table 1 presents detailed demographic information for both Samples A and B.

Measures

Demographic Covariates

Students' grade levels, racial and ethnic identities, gender identities, sexual orientations, living conditions, parents' education, and English language status were included in the analyses because previous research has documented the impact of these social conditions on adolescents' psychological health (e.g., Renshaw et al., 2024). Students were asked to identify their gender using four response options (male, female, nonbinary, or another identification). Nonbinary and other identifications were included in the same gender group. They were also asked to identify their sexual orientation from six categories (straight, gay or lesbian, bisexual, unsure, something else, or declined to respond). Those who chose *unsure*, *something else*, or *declined to respond* were treated as missing data for sexual orientation. For racial and ethnic identity, students could select from American Indian/Alaskan Native, Asian, Black or African American, Native Hawaiian or Pacific Islander, White, Latinx, or Other, with the option to choose multiple identities. Students who selected more than one category were categorized as Mixed Race. Living conditions were classified as *home with parents/guardians* or *other living arrangements* (i.e., another relative, a home with more than one family, a friend's house, foster care, a group home, a hotel, a motel, a shelter, a car, temporary housing, or another arrangement). Parents' education was categorized as *college or above,* or *below college* (i.e., did not finish high school, graduated high school, attended some college). Finally, students indicated their English language status by reporting whether they participated in an English language program. Students who indicated they *did not know* their living conditions and English language program were treated as missing.

Profile Indicators: California School Wellness Index (CSWI)

The CSWI is a 10-item measure developed based on the DFM framework (Furlong et al., 2024; Table SI 5). The CSWI assesses students' mental health across empirically related but distinct dimensions of life satisfaction and emotional distress, yielding a single composite score. The items in CSWI are from the Brief Multidimensional Student Life Satisfaction Scale (BMSLSS; Huebner et al., 2006) and the Social Emotional Distress Survey-Brief (SEDS-Brief; Dowdy et al., 2018). The students' BMSLSS and the SEDS-Brief responses were used as profile indicators. Additionally, as described by Furlong et al. (2024), the students' BMSLSS summed responses (0-25) were combined with the summed (reversed-scored) SEDS-Brief responses (0-15) to form a global wellness CSWI index with values ranging from 0-40, with higher values reflecting positive wellbeing. CSWI index value percentile ranks were derived from an independent normative sample of more than 625,000 California students in Grades 6-12 (Furlong et al., 2024).

The Brief Multidimensional Student Life Satisfaction Scale (BMSLSS)

The BMSLSS (Huebner et al., 2006; Riemer et al., 2012; Seligson et al., 2003) asks students to rate their satisfaction in five domains: family, friends, school, myself, and neighborhood/environment on a six-point response scale (0 = *very dissatisfied*, 1 = *dissatisfied*, 2 = *a little dissatisfied*, 3 = *a little satisfied,* 4 = *satisfied,* and 5 = *very* *satisfied)*. This scale has demonstrated acceptable internal reliability with an alpha coefficient of .80 and has been validated for its construct validity (Furlong et al., 2024; Hashim & Areepattamannil, 2017; Huebner et al., 2011; Seligson et al., 2003). In a study involving an independent sample of 626,940 students from grades 6-12, Furlong et al. (2024) reported an identical alpha coefficient of .80 and an omega coefficient of .83, along with a one-year stability coefficient of .58. For the overall sample in the current study, the alpha coefficient was found to be .83.

Social Emotional Distress Survey-Brief (SEDS-Brief)

The SEDS-Brief (Dowdy et al., 2018, 2023) evaluates students' experiences of emotional distress and stress over the past month. It consists of five items:

1. Difficulty getting excited (It was hard for me to get excited about anything)
2. Feeling sad (I felt sad and down)
3. Difficulty relaxing (I had a hard time relaxing)
4. Trouble coping (It was hard for me to cope, and I thought I would panic)
5. Feeling irritated (I was easily irritated).

A recent study validated the five-item (SEDS-Brief) using data from an independent sample of 113 secondary schools in California (Dowdy et al., 2023). The scale demonstrated adequate validity, as evidenced by its correlations with various indicators of well-being. It also demonstrated satisfactory internal consistency, with a Cronbach's alpha of .89 and omega coefficient of .90 (the alpha coefficient was .88 for the present study). The stability of the scale over time was confirmed by a one-year stability coefficient of .52. Furthermore, a significant negative correlation of -0.67 was observed between the SEDS-Brief and the Brief Multidimensional Student Life Satisfaction Scale (BMSLSS) (Dowdy et al., 2023; Furlong et al., 2024).

Distal Outcomes: Psychological Functioning

Students' psychological functioning was evaluated using two widely used single-item indicators of mental health problems from the Youth Risk Behavior Surveillance Survey (YRBS; Verlenden et al., 2024): persistent depressed and hopeless mood over the past year, and suicidal ideation. The question regarding persistent depressed and hopeless mood was: "In the past 12 months, did you ever feel so sad or hopeless almost every day?" For suicidal thoughts, the question was: "In the past 12 months, did you ever seriously consider attempting suicide?" Students answered "yes" or "no" to both questions (Centers for Disease Control and Prevention, 2022). Although documentation on the reliability of the YRBS items is limited, Jones et al. (2024) reported on the two-week response stability among

588 adolescents in grades 9-12. The Kappa coefficients for chronic sadness and suicidal ideation from time 1 to time 2 were .73 and .78, respectively, indicating substantial stability.

Distal Outcomes: Academic Functioning

Perceived school connectedness and self-reported academic grades and attendance indicated students' academic functioning.

School Connectedness

A five-item scale (Furlong et al., 2011) assessed students' perceived connectedness (Too et al., 2022). Students responded to a five-point response scale (1 = *strongly disagree*, 2 = *disagree*, 3 = *neither agree nor disagree*, 4 = *agree*, and 5 = *strongly agree*). An example item is, "*I feel close to people at this school*." The internal reliability of the scale for Sample B, as measured by the Omega value, was .83.

Academic Grades

Students were asked to report the grades they received in the past year. They could select from one of the eight options (1 = *mostly A's* to 8 = *mostly F's*). The item was reverse-coded; thus, a higher value represents better academic achievement.

School Absence

Students were asked how often they missed an entire school day in the past 30 days. Four options were provided (1 = *I did not miss any days of school*, 2 = *1 day*, 3 = *2 days*, 4 = *3 or more days*). A higher value indicates a higher rate of absence.

Missing Data

The rate of missing responses to the items measuring the profile indicators on Sample A ranged from 0.4% to 1.9%, and Sample B ranged from 0.4% to 1.8%. There were missing values on distal outcomes, ranging from 0.1% to 0.9%, in Sample B. Regarding the missingness of the demographic variables, the missing rates were all under 1.6% for both Samples A and B. When missingness is under 5%, it is suggested that it has negligible effects on estimates (Dong & Peng, 2013); thus, we did not conduct further analysis on missing data. All models were estimated using maximum likelihood estimation with robust standard errors (MLR) in Mplus 8.4 (Muthén & Muthén, 2017), under the missing-at-random (MAR) assumption (Enders, 2010). Full information maximum likelihood (FIML) handled missing data.

Data Analysis Plan

The analysis consisted of three steps: (a) estimating the latent profile model using a calibration and validation procedure on Samples A and B, (b) estimating profiles' relations with covariates and distal outcomes, and (c) mapping emergent latent profiles on CSWI scores distribution.

Latent Profile Model Development

We selected the optimal latent profile model using a calibration and validation procedure. As Schmiege et al. (2018) recommended, all models, ranging from 1-class to 7-class, with different model structures, were estimated on Samples A and B. We used the 10 raw scores from the CSWI items to estimate 1-to 7-class LPA models on Samples A and B. Because latent profiles may differ not only in their indicator means but also in their variances and covariances (Masyn, 2013), we evaluated five model structures—the baseline model (Model 1), in which the indicator variances are constrained to be equal across profiles. We then tested alternative specifications, including a model with indicator covariances estimated at the overall level (Model 1a), a model with variances freely estimated within each profile (Model 2), a model with covariances freely estimated within each profile (Model 3), and a model with both variances and covariances freely estimated within each profile (Model 4). Further details on the LPA model specifications can be found in Masyn (2013). The optimal model was selected based on the relative fit indices of the plausible competing models, as well as their conceptual and theoretical merits, and the meaning of the profiles (Masyn, 2013).

Several indices were used to compare the model fit across models (Masyn, 2013; Nylund-Gibson et al., 2023). The fit statistics were Bayesian information criterion (BIC), sample size adjusted BIC (saBIC), consistent Akaike information criterion (CAIC), approximate weight of evidence criterion (AWE), bootstrap likelihood ratio test (BLRT; McLachlan & Peel, 2000), and Vuong–Lo–Mendell–Rubin LRT (VLMR-LRT; Vuong, 1989). Lower information criterion values indicate a better model fit among the compared models (Nylund et al., 2007). The BLRT and the VLMR-LRT tests compare the fit of a k-class model with a $k-1$ class solution. Significant p values ($p < .05$) suggest there is evidence supporting the *k-class* solution compared to the $k-1$ class model (Nylund, 2007). For the validation step, we increasingly constrained the means, variances, and covariances of the indicators to be equivalent using a multiple-group framework (Schmiege et al., 2018). Nested models were compared via Satorra-Bentler log-likelihood ratio difference tests and sample size-adjusted BIC values (Whittaker & Miller, 2021). The validation procedure can augment the confidence in selecting the optimal model and assess the generalizability of the chosen model (Masyn, 2013; Whittaker & Miller, 2021).

Profiles' Associations with Covariates and Distal Outcomes

After confirming the final model for this study, we employed a 3-step manual approach to examine the association between profiles and students' psychological and academic functioning (Nylund-Gibson & Choi, 2018). Demographic variables (i.e., students' race and ethnicity, grade levels, gender identity, sexual orientation, living conditions, parents' education, and participation in the English language program) were included in the model to control their effects on latent profiles and distal outcomes. They were grand-mean centered. We used pairwise Wald tests to assess the significance of the estimated mean differences in outcomes between profiles.

Results

Table SI 6 shows the descriptive statistics and correlations of the central study variables. All the life satisfaction and distress items had slight to moderate correlations. Life satisfaction items were mildly and positively correlated with academic grades and school connectedness and negatively correlated with persistent hopelessness, suicidal thoughts, and absence. Distress items were positively associated with persistent hopelessness, suicidal thoughts, and absence, as well as negatively related to academic grades and school connectedness.

Model Selection

Table 2 shows the fit statistics of each model estimated on Samples A and B. The fit statistics were similar across both samples. Models 2 to 4 did not converge. Comparing the converged models, Model 1a exhibited lower information criteria statistics than Model 1 across the solutions, suggesting that Model 1a provided a better fit for the data. In Model 1a, the VLMR-LRT and BLRT were significant in all solutions, and the information criteria decreased for each additional profile. However, the magnitude of the decrease became smaller after the 3-profile solution. The 3-profile model was also replicated in the validation procedure, supported by the nonsignificant adjusted likelihood ratio difference test (see Table SI 7). Considering the relative fit statistics, validation results, theoretical relevance, and the fit with dual continua/DFM approaches, as well as the principle of parsimony, a 3-profile solution of Model 1a was selected as the optimal model. The solution demonstrated good classification accuracy with an entropy value of 0.996.

Figure 1 illustrates the three-profile solution patterns and corresponding profile sizes. The CSWI profiles were labeled (a) *Flourishing*, (b) *Moderate*, and (c) *Troubled* based on the patterns of the 10 profile indicators and referencing the classic DFM mental health categories (Suldo & Shaffer, 2008). The Flourishing profile was characterized by above-average life satisfaction and below-average distress in the past month and was the largest (Sample A: 64%). The Moderate profile (Sample A: 19%) was indicated by approximately average life satisfaction and slightly above-average distress. The Troubled profile (Sample A: 17%) featured below-average life satisfaction and above-average distress; all the distress indicators were one standard deviation above the means of the overall sample.

Demographic Correlates of CSWI Profiles

Table SI 8 presents the demographic correlates of the latent profiles, using the Troubled profile as the reference group. Compared with students in the Troubled profile, those in the Flourishing profile were more likely to be in lower grade levels, identify as male, identify as straight, live with parents or caregivers, and have parents who have graduated from college. Compared with students in the Troubled profile, students in the Moderate profile were more likely to identify as male but less likely to identify as Mixed Race, other gender identities, or lesbian/gay. They were also less likely to have parents who had graduated from college.

Profiles' Association with Distal Outcomes

Table 3 presents the thresholds and means of all outcomes for the three CSWI profiles, revealing significant differences. Students in the Flourishing profile showed the lowest likelihood of persistent depressed and hopeless mood and suicidal thoughts in the past year, with only 2.5% reporting persistent hopelessness and 0.04% reporting suicidal thoughts. In contrast, in the Moderate profile, 34.5% felt persistently depressed and hopeless, and 2.4% had suicidal thoughts. Students in the Troubled profile reported the highest rates, with 85.0% experiencing persistent hopelessness and 20.6% reporting suicidal thoughts. A similar pattern emerged for academic functioning. Students in the Flourishing profile reported the highest levels of self-reported academic performance and school connectedness, as well as the lowest absence rate, followed by those in the Moderate profile. Students in the Troubled profile had the highest absence rate and the lowest academic performance.

Discussion

This study aimed to clarify and enhance the application of the DFM mental health framework in schools by addressing several long-standing measurement challenges. There is a growing consensus on the importance of assessing psychological distress and well-being (Greenspoon & Saklofske, 2001; Suldo & Shaffer, 2008). However, much of the existing DFM literature has relied on unstandardized tools, inconsistent cut-score methods, or small sample sizes, which limit the generalizability and practical application of the findings (Antaramian et al., 2010; Lyons et al., 2012; Zhang et al., 2025). In this study, we applied LPA to the CSWI, a co-normed tool designed explicitly for DFM research. This approach enhances the field's ability to identify empirically grounded mental health profiles among students using population-based data. We identified three robust profiles: Flourishing, Moderate, and Troubled. These findings offer new insights into the intersection of wellness and distress across large samples of adolescents, helping to bridge the gap between theoretical models and practical applications in school settings.

The findings highlight the urgent need to address the youth mental health crisis, as a significant number of high school students report feelings of sadness, with nearly a quarter considering suicide (Centers for Disease Control and Prevention, 2022). Around 20% of school-age children may meet the criteria for a mental health disorder (Costello et al., 2003), and this study showed that 17% of students fell into the Troubled profile, indicating high levels of hopelessness and suicidal thoughts. Alarmingly, only a small fraction of those in need receive school-based mental health services (Walker et al., 2014), emphasizing the need for early detection and intervention (Hoover & Bostic, 2021). Utilizing universal mental health screening tools, such as the CSWI, within a data-driven framework can enhance student well-being and alleviate psychological distress (Zabek et al., 2023).

Major Findings

In contrast to prior DFM literature that used traditional cut-point methods to identify four distinct groups (Antaramian et al., 2010; DiLeo et al., 2022; González et al., 2023; Grych et al., 2020; Hermann et al., 2024; Jefferies et al., 2023; Kelly et al., 2012; King et al., 2021; Lyons et al., 2012; Renshaw et al., 2024; Xiong et al., 2017), our LPA results support a three-profile model: Flourishing (64%), Moderate (19%), and Troubled (17%). While the Flourishing and Troubled profiles closely align with those identified through traditional approaches, the Moderate group emerged as a distinct category specific to the LPA analysis. For instance, rather than identifying separate Symptomatic but Content or Vulnerable groups, the Moderate group in our findings reflects individuals with a moderate likelihood of experiencing persistent depressed mood, hopelessness, and suicidal thoughts. Results from this study, combined with previous LPA studies, suggest that there are not four "true" groups of student mental health; instead, the four groups frequently formed within DFM research are an artifact of the cut-point approach used to create dual-factor groupings. However, regardless of the approach (i.e., LPA vs. cut-point approach) used to examine DFM mental health, there is generally an easily identifiable "top" group with strong indicators of student well-being and an easily recognizable "bottom" group with strong indicators of student distress.

The appearance of a "middle" or Moderate class is not unprecedented in DFM studies employing LPA (Chen et al., 2025; Gregory et al., 2024; Maurer et al., 2025; Moore et al., 2019; Sechague Monroy et al., 2024; Zhang et al., 2025). The number of "middle" classes may vary across LPA studies, depending on the measures used and the complexity of the indicators considered in the analysis. This variation likely reflects the nature of the LPA methodology, which identifies classes based on empirical data rather than predefined categories. The LPA process is inherently complex, considering multiple criteria including statistical fit indices, theoretical, and substantive factors (Spurk et al., 2020).

The ongoing discussion about classification frameworks and the characteristics of DFM classes indicates that adolescents' responses might be grouped into three, four, five, or six distinct categories. Various methodologies have yielded different results. However, even with a large sample size using a co-normed measure of well-being and distress, the LPA classes identified in the present study did not align with the traditional four DFM mental health groups.

Implications and Future Directions for Research

LPA is a statistical method used to identify unobserved subgroups within a population based on continuous data (Spurk et al., 2020). This approach is beneficial for understanding mental health patterns among young people (Petersen et al., 2019). While LPA effectively uncovers distinct patterns and profiles, it has limitations, especially when detecting multiple low-incidence profiles. This limitation means that important clinical patterns may go unnoticed in LPA analyses—not because they are absent but because these profiles do not generate strong enough signals within the dataset to be recognized. Therefore, researchers should proceed cautiously and consider using alternative methods or supplementary analyses to ensure that subtle yet meaningful variations in the data are not overlooked.

In our study, we used the CSWI. We found that the low frequency of response patterns in the extreme lower left (vulnerable) and upper right (symptomatic by content) quadrants of the DFM response array indicates that there are insufficient students to classify these patterns as unique profiles. Although the present analysis does not eliminate the possibility that specific students may be experiencing feelings of languishing or other symptoms, it is important to recognize that the nature of these response patterns, combined with the limited number of such cases, makes them challenging to identify distinctly in comparison to the overall responses of all students.

The possibility of dividing the moderate mental health classification into additional subclasses using LPA should be scrutinized. This refinement could enhance the ability of care coordination teams to identify which students need follow-up support after administering schoolwide surveys across various districts. One notable implication of this approach is that if forthcoming latent profile research seeks to identify additional classes that presumably manifest less frequently, larger, more representative population-based samples will be necessary. This methodological shift is crucial for enhancing the capacity to detect such patterns effectively. Additionally, the procedures used to develop the CSWI could be replicated with other wellness and distress measures with more items to assess various types of wellbeing (e.g., affective, psychological, and social) or additional types of mental health problems (e.g., externalizing and internalizing distress), which could serve as broader indicators of mental wellbeing and distress. Different measures might yield a more varied distribution of responses, potentially revealing distinct classes through LPA. Such investigations may reveal additional factors, including the possibility that some elements are merged, organized, or associated with more intricate profiles that occur less frequently within the population. While our discussion highlights the potential benefits of this approach, it is also essential to acknowledge the practical implications of using longer surveys within a schoolwide screening context.

The lack of a standardized procedure makes researching the number of meaningful DFM classes challenging. This situation highlights the need for clarity and consistency in classification methodologies, as uniformity is essential for improving understanding and application in DFM research. The guiding principles for determining the number of classes should focus on three key areas: empirical evidence, clinical relevance, and resource availability.

The number of DFM classes required may vary depending on the specific objectives of the research or clinical practice. Therefore, decisions should not rely solely on empirical data; they must also consider the context and goals of the study or clinical application. The primary question is how many classes are necessary to effectively inform and guide appropriate, cost-effective follow-up check-ins and support. By balancing these factors, the field could develop a classification system that is both practical and effective in achieving the desired outcomes.

Implications and Future Directions for Practice

The use of LPA for school-based screening to plan for individualized supports and interventions is not practical. Practitioners and most researchers alike lack the skills to apply LPA results to school-based screening. As such, the practical implications of this study are to inform screening efforts without requiring the use of sophisticated statistical analyses. One of the foremost practical implications is the need for a continued focus on dual-factor approaches to understanding student wellbeing. The review of the DFM literature, combined with the results of this study, highlights the importance of inquiring about students' symptomatology and well-being. Asking questions that are broadly applicable to all students as opposed to solely screening for problem conditions that may only be experienced by a minority of students (i.e., screening for risk as opposed to screening for major depressive disorder) offers a more comprehensive approach to complete mental health screening (Moore et al., 2015).

While the current study's results may not be dramatic, they hold practical value. DFM is not a diagnostic tool, but rather a categorical scheme used to identify broad categories of mental wellness. One of its primary uses is to support screening and monitoring rather than to describe clinically meaningful diagnostic categories. The three identified classes in this study provide essential information for conducting schoolwide mental health screenings. Specifically, these categories help identify students with strong mental health and highlight those requiring follow-up care. Regardless of the classification approach or sample used, results consistently reveal a low or Troubled group of students. Given that students in this Troubled group consistently experience poor associated outcomes (e.g., increased symptoms of depression and suicidality), school-based mental health professionals must follow up with this group of students. For example, the Troubled class should represent a percentage that a care team can realistically follow up on. Our study found that 17% (raw score of 19, within the 0-40 range of the CSWI) provided a reasonable range for the care team to initially review and prioritize access to available services, while evaluating whether additional services were necessary. These results offer initial guidance for prioritizing follow-up check-ins for student care. Consistent with multiple-gating screening procedures, further assessment or early intervention efforts are likely warranted for this group of students. Additionally, regardless of the classification approach used, the largest group or class of students consistently appears to be thriving or Flourishing. In this study, 64% of the students were characterized as Flourishing, based on reports of above-average life satisfaction and low levels of distress.

The middle or Moderate groups provide the most interesting findings among all LPA and cut-score DFM approaches. The field requires guidance and standardization of procedures for addressing the significant group of students in the middle classes or profiles to enhance prevention and intervention decisions within multi-tiered frameworks. Only by gaining a deeper understanding of the unique characteristics of students within these middle groups can schools tailor services to meet their individual needs. A potential area of research to explore is the differentiation of students within the moderate mental health group. Further research could clarify the distinctions among these middle-range students, enabling the identification of individuals who may benefit from follow-up evaluations and support. Much more work is needed to standardize DFM classification approaches to inform student support services.

The emergence of additional classes beyond Flourishing, Moderate, and Troubled could offer a lower threshold to guide follow-up assessment and early intervention after the Troubled class. However, we note that this is not essential due to the nature of the classes being ordered (i.e., high, moderate, low) and because the CSWI ranks the responses across one 0-40 scale with higher scores indicative of more optimal mental health; this allows for student care teams to start by following up with students in the lowest 5%, 10% or another percentage of a school's distribution. Our

LPA profile evaluation supports this observation, indicating that the most consistent finding is that the largest classes exhibit an ordered LPA class relationship. Further research is needed to explore the generalizability of LPA-identified ordered classes. However, while other unordered classes may be identified, existing LPA studies suggest that these occur at low frequencies and may be associated with multidimensional measures of wellness and distress.

When categorizing student behaviors, it is essential to recognize the limitations of simplifying mental health experiences into a few distinct groups. Such an oversimplification can undermine the rich and diverse realities that students face. From a clinical perspective, mental health conditions are diagnosed based on standardized criteria outlined in systems like the International Classification of Diseases (ICD) or the Diagnostic and Statistical Manual of Mental Disorders (DSM). These guidelines emphasize that their prevalence in the population does not solely determine clinical patterns but is defined by specific symptomatic features meticulously outlined in comprehensive clinical manuals. This nuanced understanding allows a more accurate and compassionate approach to mental health and student experiences. It is crucial to clarify that the DFM model is not a prerequisite for identifying new mental health conditions. While the DFM sheds light on current symptom characteristics, it should not be seen as a replacement for the well-established clinical definitions meticulously crafted through rigorous research and practical experience. Maintaining these definitions ensures clarity and consistency in diagnosing and treating mental health disorders, vital for clinical efficacy and patient care.

Ultimately, the specific number of mental health categories identified—whether three, four, or five—is of secondary significance compared to the role of these assessments as preliminary screening tools. The primary objective of these evaluations is to function as an initial filter for follow-up actions, highlighting the necessity for a standardized procedure in their implementation and assessment. In assessments designed to categorize students' strengths and weaknesses, it is crucial to recognize that certain variables may not be emphasized in an LPA; however, this does not diminish their existence or relevant significance. These assessments are intended for universal screening purposes, facilitating subsequent educational interventions rather than exhaustively outlining every possible pattern of strengths and weaknesses. In other words, the DFM is not a diagnostic tool but a scheme to identify broad categories. One of its primary uses is to support mental health screening and monitoring rather than to propose clinically meaningful diagnostic categories. As such, the CSWI is offered as one tool explicitly designed with DFM research in mind, featuring co-normed measures of both life satisfaction and distress. The CSWI can support school-based screening efforts.

Limitations

Among the limitations of the present study, it is essential to highlight that the CSWI utilized in these analyses exclusively focuses on internalizing stress indicators and overlooks adolescents' externalizing behavioral symptoms. This omission means the current analysis does not encompass the complete spectrum of behaviors addressed in the original Greenspoon and Saklofske (2001) study. Furthermore, the findings do not consider previous research indicating the importance of evaluating externalizing behavioral symptoms independently, particularly when placed within the DFM framework (Zakszeski et al., 2025). However, as researchers further consider students with externalizing behavioral symptoms, it is instructive to reconsider Greenspoon and Saklofske's (2001) original conceptualization, as they employed a unique conceptual framework when examining students who would later be categorized as symptomatic yet content. Despite exhibiting higher behavioral problem symptoms, they proposed a group of adolescents who reported greater life satisfaction and overall well-being. In this context, they suggested that for some students with heightened behavioral problems, their elevated well-being might stem from the protective effects associated with a more robust self-identity linked to psychopathy and self-affirming tendencies. Thus, distinct hypotheses regarding the interplay between student distress and well-being types informed the conceptual bases for proposing the vulnerable and symptomatic content groups. Consequently, researchers interested in integrating behavioral problem items within a dual-factor model screening framework may find it beneficial to revisit Greenspoon and Saklofske's (2001) original conceptualizations and assess students' internalizing and externalizing profiles separately.

We acknowledge the limitations of our current study and emphasize the need for additional research on DFM. Incorporating a brief externalizing behavioral assessment in future studies is particularly important. Additionally, reevaluating the methodology used to establish cut points for categorizing DFM groups is essential for creating a more streamlined self-report behavioral measure. The traditional cut-point method for DFM identifies "high distress" as elevated responses in internalizing, externalizing, or both areas. This results in hybrid symptomatic but content (SBC) groups, which complicates cross-sample comparisons. Therefore, a comprehensive reassessment of these classifications is crucial to enhance their clarity and applicability in future research efforts.

Conclusions

The current study highlights the complexities and challenges involved in identifying and categorizing youth mental health within the framework of the DFM. The findings suggest that the DFM groups have not been established as distinct entities; instead, they are primarily a consequence of the algorithm employed in their creation. Furthermore, the labels assigned to the four classic DFM categories—CMH, SBC, Vulnerable, and Troubled—have not been consistently replicated using empirical methods. Consequently, these labels may oversimplify or misrepresent the diverse experiences of young individuals encountering varying degrees of mental health challenges.

The limitations of the cut-point and LPA approaches in DFM research underscore the need for standardized measurement methods to advance the field. Standardization would enhance the comparability of research findings, facilitate the integration of diverse data, and foster clarity and replication in studies. The CSWI examined in this study is one option for researchers and practitioners to evaluate and consider. Beyond standardizing measurements, reaching a consensus on creating DFM categories would improve the integration of research efforts and ultimately strengthen support systems for all young people, particularly those facing mental health challenges.

References

Achenbach, T. M., & Rescorla, L. A. (2001). Child Behavior Checklist for Ages 6-18. *APA PsycTests.* https://doi.org/10.1037/t47452-000

Antaramian, S. P., Scott Huebner, E., Hills, K. J., & Valois, R. F. (2010). A dual-factor model of mental health: Toward a more comprehensive understanding of youth functioning. *The American Journal of Orthopsychiatry, 80*(4), 462–472. https://doi.org/10.1111/j.1939-0025.2010.01049.x

Centers for Disease Control and Prevention (2022). *Youth Risk Behavior Survey: Data summary & trends report 2011-2021*. https://stacks.cdc.gov/view/cdc/124928

Chen, R., Gao, X., Zhang, Z., Hong, M., & Zhang, L. (2025). What predicts mental health profiles in first-generation college freshmen? The role of proactive personality and university environment. *BMC Psychology, 13*(1), 166. https://doi.org/10.1186/s40359-025-02498-2

Clark, K. N., Blyth, G., Plant, M., Wilson, K., & Malecki, C. K. (2024). Dual-factor mental health in adolescence: Comparing classification methods. *Journal of School Psychology, 107*, 101391. https://doi.org/10.1016/j.jsp.2024.101391

Clark, K. N., & Malecki, C. K. (2022). Adolescent mental health profiles through a latent dual-factor approach. *Journal of School Psychology, 91,* 112–128. https://doi.org/10.1016/j.jsp.2022.01.003

Costello, E. J., Mustillo, S., Erkanli, A., Keeler, G., & Angold, A. (2003). Prevalence and development of psychiatric disorders in childhood and adolescence. *Archives of General Psychiatry, 60*(8), 837–844. https://doi.org/10.1001/archpsyc.60.8.837

DiLeo, L. L., Suldo, S. M., Ferron, J. M., & Shaunessy-Dedrick, E. (2022). Three-wave longitudinal study of a dual-factor model: Mental health status and academic outcomes for high school students in academically accelerated curricula. *School Mental Health, 14*(3), 514–530. https://doi.org/10.1007/s12310-021-09497-9

Dong, Y., & Peng, CY.J. (2013). Principled missing data methods for researchers. *SpringerPlus 2,* 222. https://doi.org/10.1186/2193-1801-2-222

Dowdy, E., Furlong, M. J., Nylund-Gibson, K., Arch, D., Hinton, T., & Carter, D. (2023). Validating a brief student distress measure for schoolwide wellness surveillance. *Assessment for Effective Intervention, 48*(3), 159–169. https://doi.org/10.1177/15345084221138947

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

Dowdy, E., Ritchey, K., & Kamphaus, R. W. (2010). School-based screening: A population-based approach to inform and monitor children's mental health needs. *School Mental Health, 2*(4), 166–176. https://doi.org/10.1007/s12310-010-9036-3

Enders, C. K. (2010). *Applied missing data analysis.* Guilford Press.

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., O'Malley, M., Chan, M., Dowdy, E., Goodwin, J. W., Ortiz, A., Nylund-Gibson, K., & Hanson, T. (2024). The California Student Wellness Index: Development, validation, and multi-tier applications. *Contemporary School Psychology*. https://doi.org/10.1007/s40688-024-00519-2

González, M., Correa, C., Ruíz, S., & Barroso, E. (2023). El Modelo de Factor Dual de Salud Mental en adolescentes: Relevancia de los factores intrapersonales y contextuales de protección y riesgo. *Psicología y Salud, 33*(2), Article 2. https://doi.org/10.25009/pys.v33i2.2830

Greenspoon, P. J., & Saklofske, D. H. (2001). Toward an integration of subjective well-being and psychopathology. *Social Indicators Research, 54*(1), 81–108. https://doi.org/10.1023/A:1007219227883

Gregory, T., Monroy, N. S., Grace, B., Finlay-Jones, A., Brushe, M., Sincovich, A., Heritage, B., Boulton, Z., & Brinkman, S. A. (2024). Mental health profiles and academic achievement in Australian school students. *Journal of School Psychology, 103*, 101291. https://doi.org/10.1016/j.jsp.2024.101291

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, 90*(4), 458–467. https://doi.org/10.1037/ort0000449

Hashim, J., & Areepattamannil, S. (2017). The Brief Multidimensional Students' Life Satisfaction Scale (BMSLSS): Reliability, validity, and gender invariance in an Indian adolescent sample. *Journal of Adolescence, 57,* 54–58. https://doi.org/10.1016/j.adolescence.2017.03.007

Hermann, V., Söderqvist, F., Karlsson, A-C., Sarkadi, A., & Durbeej, N. (2024). Mental health status according to the dual-factor model in Swedish adolescents: A cross-sectional study highlighting associations with stress, resilience, social status, and gender. *PLOS ONE, 19*(3), e0299225. https://doi.org/10.1371/journal.pone.0299225

Hoover, S., & Bostic, J. (2021). Schools as a vital component of the child and adolescent mental health system. *Psychiatric Services, 72*(1), 37–48. https://doi.org/10.1176/appi.ps.201900575

Huebner, E. S. (1991). Correlates of life satisfaction in children. *School Psychology Quarterly, 6*(2), 103–111. https://doi.org/10.1037/h0088805

Huebner, E. S. (1994). Preliminary development and validation of a multidimensional life satisfaction scale for children. *Psychological Assessment, 6*(2), 149–158. https://doi.org/10.1037/1040-3590.6.2.149

Huebner, E. S., Suldo, S. M., & Gilman, R. (2006). Life Satisfaction. In G. G. Bear & K. M. Minke (Eds.), *Children's needs III: Development, prevention, and intervention* (pp. 357–368). National Association of School Psychologists.

Iasiello, M., & van, A. J. (2020). Mental health and/or mental illness: A scoping review of the evidence and implications of the dual-continua model of mental health. *Evidence Base: A Journal of Evidence Reviews in Key Policy Areas, 1*, 1–45. https://doi.org/10.3316/informit.261420605378998

Jefferies, P., Fritz, J., Deighton, J., & Ungar, M. (2023). Analysis of protective factors in schoolchildren in England using the dual-factor model of mental health. *Research on Child and Adolescent Psychopathology, 51*(7), 907–920. https://doi.org/10.1007/s10802-023-01038-z

Jiang, Y., Ding, C., & Shen, B. (2023). Latent profile analysis of mental health among Chinese university students: Evidence for the dual-factor model. *Healthcare, 11*(20), Article 20. https://doi.org/10.3390/healthcare11202719

Jones, S. E., Brener, N. D., Queen, B., Hershey-Arista, M., Harris, W. A., Mpofu, J. J., & Underwood, J. M. (2024). Reliability of the 2021 National Youth Risk Behavior Survey Questionnaire. *American Journal of Health Promotion, 38*(6), 843–851. https://doi.org/10.1177/08901171241239735

Kelly, R. M., Hills, K. J., Huebner, E. S., & McQuillin, S. D. (2012). The longitudinal stability and dynamics of group membership in the dual-factor model of mental health: Psychosocial predictors of mental health. *Canadian Journal of School Psychology, 27*(4), 337–355. https://doi.org/10.1177/0829573512458505

Kenny, R., Dooley, B., & Fitzgerald, A. (2013). Interpersonal relationships and emotional distress in adolescence. *Journal of Adolescence, 36*(2), 351–360. https://doi.org/10.1016/j.adolescence.2012.12.005

Keyes, C. L. M. (2006). Mental health in adolescence: Is America's youth flourishing? *American Journal of Orthopsychiatry, 76*(3), 395–402. https://doi.org/10.1037/0002-9432.76.3.395

Kieling, C., Baker-Henningham, H., Belfer, M., Conti, G., Ertem, I., Omigbodun, O., Rohde, L. A., Srinath, S., Ulkuer, N., & Rahman, A. (2011). Child and adolescent mental health worldwide: Evidence for action. *The Lancet, 378*(9801), 1515–1525. https://doi.org/10.1016/S0140-6736(11)60827-1

King, N., Davison, C. M., & Pickett, W. (2021). Development of a dual-factor measure of adolescent mental health: An analysis of cross-sectional data from the 2014 Canadian Health Behaviour in School-aged Children (HBSC) study. *BMJ Open, 11*(9), e041489. https://doi.org/10.1136/bmjopen-2020-041489

Laurent, J., Catanzaro, S. J., Joiner Jr., T. E., Rudolph, K. D., Potter, K. I., Lambert, S., Osborne, L., & Gathright, T. (1999). A measure of positive and negative affect for children: Scale development and preliminary validation. *Psychological Assessment, 11*(3), 326–338. https://doi.org/10.1037/1040-3590.11.3.326

Lyons, M. D., Huebner, E. S., Hills, K. J., & Shinkareva, S. V. (2012). The dual-factor model of mental health: Further study of the determinants of group differences. *Canadian Journal of School Psychology, 27*(2), 183–196. https://doi.org/10.1177/0829573512443669

Masyn, K. E. (2013). Latent class analysis and finite mixture modeling. *The Oxford handbook of quantitative methods: Statistical Analysis*, Vol. 2 (pp. 551–611). Oxford University Press.

Maurer, M. M., Hoff, E., & Daukantaitė, D. (2025). Mental health profiles among Swedish high school students: Relationships to environmental sensitivity and coping self-efficacy. *Journal of Happiness Studies, 26*(3), 37. https://doi.org/10.1007/s10902-024-00847-3

McLachlan, G., & Peel, D. (2000). Finite mixture models. *Wiley Series in Probability and Statistics.* http://dx.doi.org/10.1002/0471721182

Moore, S. A., Dowdy, E., Nylund-Gibson, K., & Furlong, M. J. (2019). An empirical approach to complete mental health classification in adolescents. *School Mental Health, 11*(3), 438–453. https://doi.org/10.1007/s12310-019-09311-7

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,* 253–267. https://doi.org/10.1007/s40688-015-0062-x

Muthén, L. K., & Muthén, B. O. (2017). *Mplus statistical analysis with latent variables user's guide* (eighth edition).

Authors. https://www.statmodel.com/download/usersguide/MplusUserGuideVer_8.pdf

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Nylund-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science, 4*(4), 440–461. https://doi.org/10.1037/tps0000176

Nylund-Gibson, K., Garber, A. C., Carter, D. B., Chan, M., Arch, D. A. N., Simon, O., Whaling, K., Tartt, E., & Lawrie, S. I. (2023). Ten frequently asked questions about latent transition analysis. *Psychological Methods, 28*(2), 284–300. https://doi.org/10.1037/met0000486

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*. https://doi.org/10.3389/fpsyg.2019.01214

Rai, D., Kosidou, K., Lundberg, M., Araya, R., Lewis, G., & Magnusson, C. (2012). Psychological distress and risk of long-term disability: Population-based longitudinal study. *Journal of Epidemiology & Community Health, 66*(7), 586–592. https://doi.org/10.1136/jech.2010.119644

Renshaw, T. L., & Cohen, A. S. (2014). Life satisfaction as a distinguishing indicator of college student functioning: Further validation of the two-continua model of mental health. *Social Indicators Research, 117*(1), 319–334. https://doi.org/10.1007/s11205-013-0342-7

Renshaw, T., Bolognino, S., & Clark, K. (2024). Exploring a dual-factor mental health screening model with children in grades 5–10. *School Psychology.* https://doi.org/10.1037/spq0000669

Reynolds, C., & Kampaus, R. (1992). *Behavior Assessment System for Children.* Pearson.

Riemer, M., Athay, M. M., Bickman, L., Breda, C., Kelley, S. D., & Vides de Andrade, A. R. (2012). The Peabody Treatment Progress Battery: History and methods for developing a comprehensive measurement battery for youth mental health. *Administration and Policy in Mental Health and Mental Health Services Research, 39*(1), 3–12. https://doi.org/10.1007/s10488-012-0404-1

Schmiege, S. J., Masyn, K. E., & Bryan, A. D. (2018). Confirmatory latent class analysis: Illustrations of empirically driven and theoretically driven model constraints. *Organizational Research Methods, 21*(4), 983–1001. https://doi.org/10.1177/1094428117747689

Sechague Monroy, N., Brushe, M., Sincovich, A., Boulton, Z., & Gregory, T. (2024). Associations between mental health profiles and later school outcomes. *Australian Journal of Education, 68*(3), 199–223. https://doi.org/10.1177/00049441241278411

Seligman, M. E. P., Ernst, R. M., Gillham, J., Reivich, K., & Linkins, M. (2009). Positive education: Positive psychology and classroom interventions. *Oxford Review of Education, 35*(3), 293–311. https://doi.org/10.1080/03054980902934563

Seligson, J. L., Huebner, E. S., & Valois, R. F. (2003). Preliminary validation of the Brief Multidimensional Students' Life Satisfaction Scale (BMSLSS). *Social Indicators Research, 61*(2), 121–145. https://doi.org/10.1023/A:1021326822957

Shonkoff, J. P., Garner, A. S., Siegel, B. S., Dobbins, M. I., Earls, M. F., Garner, A. S., McGuinn, L., Pascoe, J., & Wood, D. L. (2012). The lifelong effects of early childhood adversity and toxic stress. *Pediatrics, 129*(1), e232–e246. https://doi.org/10.1542/peds.2011-2663

Sisk, L. M., & Gee, D. G. (2022). Stress and adolescence: Vulnerability and opportunity during a sensitive window of development. *Current Opinion in Psychology, 44*, 286–292. https://doi.org/10.1016/j.copsyc.2021.10.005

Smith, N. D. W., Suldo, S. M., Hearon, B. V., & Ferron, J. M. (2020). An application of the dual-factor model of mental health in elementary school children: Examining academic engagement and social outcomes. *Journal of Positive Psychology & Wellbeing, 4*(1), 49–68.

Spurk, D., Hirschi, A., Wang, M., Valero, D., & Kauffeld, S. (2020). Latent profile analysis: A review and "how to" guide of its application within vocational behavior research. *Journal of Vocational Behavior, 120*, 103445. https://doi.org/10.1016/j.jvb.2020.103445

Suldo, S. M., & Shaffer, E. J. (2008). Looking beyond psychopathology: The dual-factor model of mental health in youth. *School Psychology Review, 37*(1), 52–68. https://doi.org/10.1080/02796015.2008.12087908

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/SPR45-4.434-457

Too, E. K., Chongwo, E., Mabrouk, A., & Abubakar, A. (2022). Adolescent connectedness: A scoping review of available measures and their psychometric properties. *Frontiers in Psychology*, *13*, 856621. https://doi.org/10.3389/fpsyg.2022.856621

Verlenden, J., Pampati, S., Viox, M. H., Brener, N., Licitis, L., Dittus, P., & Ethier, K. (2024). Measuring population-level adolescent mental health using a single-item indicator of experiences of sadness and hopelessness: Cross-sectional study. *JMIR Formative Research, 8*(1), e54288. https://doi.org/10.2196/54288

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica*, *57*(2), 307–333. https://doi.org/10.2307/1912557

Walker, H. M., Small, J. W., Severson, H. H., Seeley, J. R., & Feil, E. G. (2014). Multiple-gating approaches in universal screening within school and community settings. In R. J. Kettler, T. A. Glover, C. A. Albers, & K. A. Feeney-Kettler (Eds.), *Universal screening in educational settings: Evidence-based decision making for schools* (pp. 47–75). American Psychological Association. https://doi.org/10.1037/14316-003

Wang, Z., Zheng, J., Wang, X., Lu, K., Liu, F., & He, J. (2025). Profiles, transitions, and influencing factors of mental health among Chinese adolescents: The Dual-Factor mental health perspective. *Current Psychology.* https://doi.org/10.1007/s12144-025-07805-z

Waters, L., & Loton, D. (2019). SEARCH: A meta-framework and review of the field of positive education. *International Journal of Applied Positive Psychology, 4*(1), 1–46. https://doi.org/10.1007/s41042-019-00017-4

Whittaker, T. A., & Miller, J. E. (2021). Exploring the enumeration accuracy of cross-validation indices in latent class analysis. *Structural Equation Modeling: A Multidisciplinary Journal, 28*(3), 376–390. https://doi.org/10.1080/10705511.2020.1802280

Xiong, J., Qin, Y., Gao, M., & Hai, M. (2017). Longitudinal study of a dual-factor model of mental health in Chinese youth. *School Psychology International, 38*(3), 287–303. https://doi.org/10.1177/0143034317689970

Zabek, F., Lyons, M. D., Alwani, N., Taylor, J. V., Brown-Meredith, E., Cruz, M. A., & Southall, V. H. (2023). Roles and functions of school mental health professionals within comprehensive school mental health systems. *School Mental Health, 15*(1), 1–18. https://doi.org/10.1007/s12310-022-09535-0

Zakszeski, B. N., Ormiston, H. E., Renshaw, T. L., Chan, M.-K., & Osgood, D. (2025). Stability, latent profiles, and sociodemographic predictors of student-rated social, emotional, and behavioral risk. *School Mental Health.* https://doi.org/10.1007/s12310-025-09757-y

Zhang, Q., Tu, Y., Yao, S., Zhang, Q., Liu, J., & Quan, P. (2025). Impact of childhood maltreatment on adolescents' mental health– a longitudinal study based on the dual-factor model. *BMC Psychology, 13*(1), 95. https://doi.org/10.1186/s40359-025-02398-5

Zhang-James, Y., Clay, J. W. S., Aber, R. B., Gamble, H. M., & Faraone, S. V. (2025). Post-COVID-19 mental health distress in 13 million youth: A retrospective cohort study of electronic health records. *Journal of the American Academy of Child & Adolescent Psychiatry, 64*(1), 65–76. https://doi.org/10.1016/j.jaac.2024.03.023

Zhou, J., Jiang, S., Zhu, X., Huebner, E. S., & Tian, L. (2020). Profiles and transitions of dual-factor mental health among Chinese early adolescents: The predictive roles of perceived psychological need satisfaction and stress in school. *Journal of Youth and Adolescence, 49*(10), 2090–2108. https://doi.org/10.1007/s10964-020-01253-7

Table 1

Demographic Characteristics of the Analytic Samples

Variable	Sample A (N = 17,358) %	Sample B (N = 17,927) %
Grade		
6	3.3	3.1
7	28.7	28.7
8	5.0	5.2
9	27.2	27.5
10	5.7	5.4
11	25.4	25.2
12	4.7	4.9
Other/Ungraded	0.04	0.1
Gender identification		
Male	49.5	49.0
Female	48.1	48.5
Other gender identity	2.4	2.5
Sexual orientation		
Straight	81.6	81.1
Lesbian or gay	2.2	2.2
Bisexual	6.5	6.7
Something else	2.1	2.3
Not sure	3.6	3.8
Decline to respond	4.0	3.9
Race and ethnicity		
American Indian, Alaskan Native	0. 8	0.7
Asian	15.5	15.6
Black, African American	3.6	3.6
Latinx	34.8	35.0
Native Hawaiian, Pacific Islander	0.5	0.5
White	19.10	19.4
Other Identification	4.2	4.1
Mixed Race	21.3	20.8
Living circumstances		
Home with 1+ parents/guardians	92.7	92.8
Other living conditions	7.3	7.2
Parent education		
College or higher	45.5	46.0
Below college, did not finish high school, high school grad, some college	35.6	36.0
Do not know	18.9	18.0
English language program		
No	78.1	78.6
Yes	7.3	7.3
Don't know	14.6	14.1

Table 2

Fit Statistics for LPA Class Enumeration

SAMPLE A (N = 17,358)									
Model 1									
Model (K-class)	LL	npar	AIC	CAIC	BIC	saBIC	AWE	VLMR-LRT *p*-value	BLRT *p*-value
1-class	-264899.906	20	529839.81	530015.05	529995.05	529931.49	530250.28	—	—
2-class	-240451.882	31	480965.76	481237.38	481206.38	481107.86	481602.00	<.001	<.001
3-class	-233183.774	42	466451.55	466819.54	466777.54	466644.07	467313.54	<.001	<.001
4-class	-226592.954	53	453291.91	453756.28	453703.28	453534.85	454379.66	<.001	<.001
5-class	-223490.732	64	447109.46	447670.22	447606.22	447402.83	448422.98	<.001	<.001
6-class	-221370.689	75	442891.38	443548.51	443473.51	443235.17	444430.65	<.001	<.001
7-class	-264899.906	86	439644.46	440397.97	440311.97	440038.67	441409.49	<.001	<.001
Model 1a									
Model (K-class)	LL	npar	AIC	CAIC	BIC	saBIC	AWE	VLMR-LRT *p*-value	BLRT *p*-value
1-class	-228246.703	40	456573.41	456923.88	456883.88	456756.76	457394.35	—	—
2-class	-221316.525	51	442735.05	443181.90	443130.90	442968.83	443781.75	<.001	<.001
3-class	**-215769.608**	**62**	**431663.22**	**432206.45**	**432144.45**	**431947.42**	**432935.68**	**<.001**	**<.001**
4-class	-214284.950	73	428715.90	429355.51	429282.51	429050.52	430214.12	<.001	<.001
5-class	-212501.278	84	425170.56	425906.55	425822.55	425555.60	426894.54	<.001	<.001

SAMPLE B (N = 17,927)

Model 1

Model (K-class)	LL	npar	AIC	CAIC	BIC	saBIC	AWE	VLMR-LRT *p*-value	BLRT *p*-value
1-class	-275256.385	20	550552.77	550728.65	550708.65	550645.09	550964.53	—	—
2-class	-248929.497	31	497920.99	498193.61	498162.61	498064.09	498559.23	<.001	<.001
3-class	-241035.110	42	482154.22	482523.57	482481.57	482348.10	483018.92	<.001	<.001
4-class	-234449.100	53	469004.20	469470.29	469417.29	469248.85	470095.37	<.001	<.001
5-class	-231555.336	64	463238.67	463801.49	463737.49	463534.10	464556.31	<.001	<.001
6-class	-229336.487	75	458822.97	459482.53	459407.53	459169.18	460367.08	<.001	<.001
7-class	-227761.974	86	455695.95	456452.24	456366.24	456092.93	457466.53	<.001	<.001

Model 1a

Model (K-class)	LL	npar	AIC	CAIC	BIC	saBIC	AWE	VLMR-LRT *p*-value	BLRT *p*-value
1-class	-236967.960	40	474015.92	474367.68	474327.68	474200.56	474839.45	—	—
2-class	-229709.401	51	459520.80	459969.30	459918.30	459756.22	460570.80	<.001	<.001
3-class	**-224174.542**	**62**	**448473.08**	**449018.32**	**448956.32**	**448759.28**	**449749.55**	**<.001**	**<.001**
4-class	-223014.727	73	446175.45	446817.42	446744.42	446512.43	447678.39	<.001	<.001

Note. K – number of classes; LL = model log likelihood; CAIC = consistent Akaike information criterion; BIC = Bayesian information criterion; saBIC = sample size adjusted BIC; AWE = approximate weight of evidence criterion; VLMR-LRT = Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test; BLRT = bootstrapped likelihood ratio test; Model 1 indicated fixed variances across profiles and no covariances specified. Model 1a specified covariances of the overall model, which did not converge after a 5-profile solution. Model 2 specified within-class variances. Model 3 specified within-profile covariances. Model 4 specified within-profile variances and covariances. Models 2 and 3 were not included because they did not converge. **Bold** = the optimal model based on empirical and conceptual merit.

Table 3

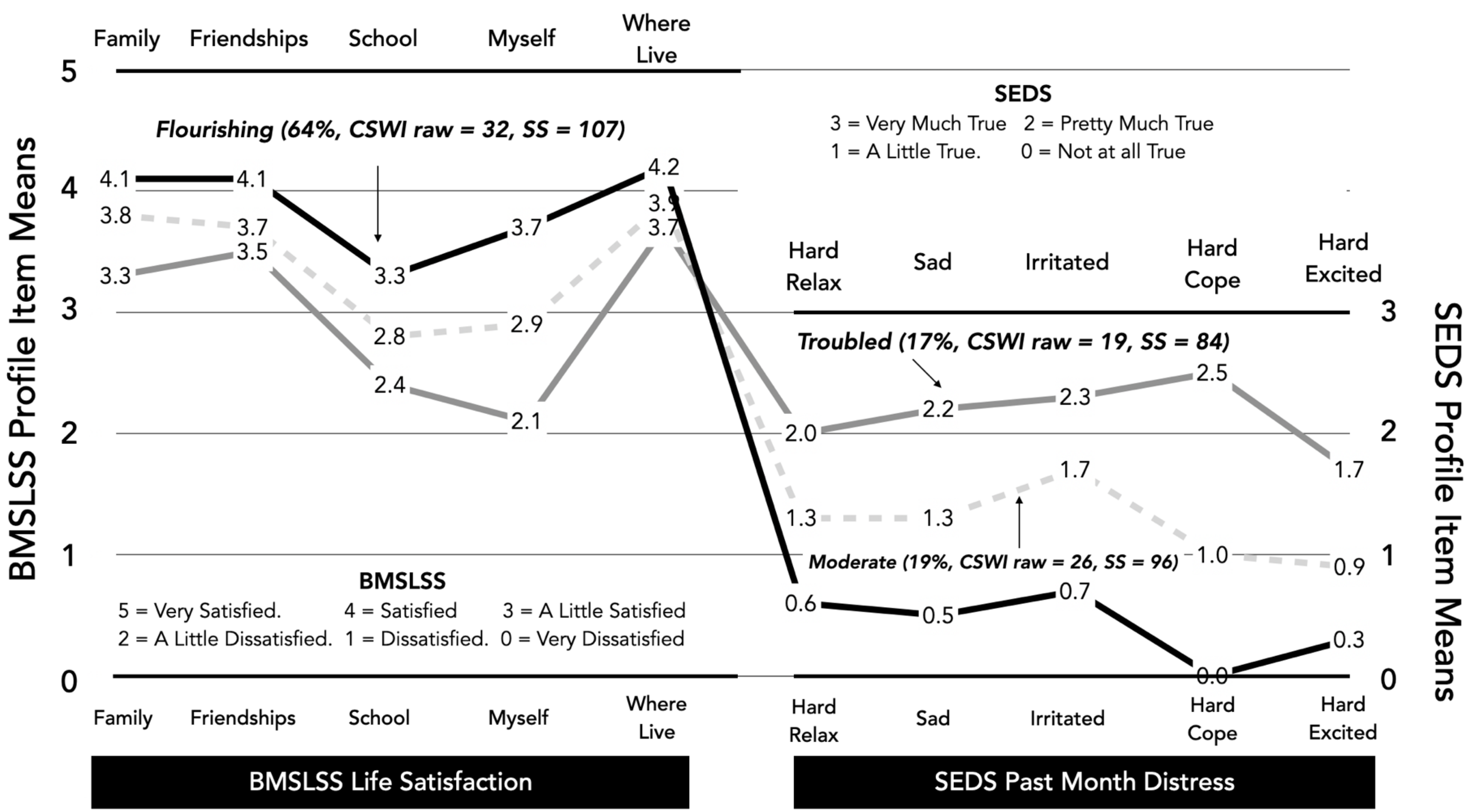
Threshold, Mean, Standard Error, and Effect Size of Distal Outcomes Across Profiles

CSWI Profiles	Persistent depressed mood	Suicidal thoughts	School connectedness	Self-report GPA	Absence
Range	0/1	0/1	1-5	1-8	1-4
	Probability / Threshold (SE)		*M (SE)*		
Flourishing	2.5% / 1.96 (.04) [a]	0.04% / 3.35 (.07) [a]	3.69 (.01) [a]	6.53 (.02) [a]	1.96 (.01) [a]
Moderate	34.5% / 0.40 (.05) [b]	2.4% / 1.98 (.07) [b]	3.47 (.02) [b]	6.44 (.03) [b]	2.07 (.02) [b]
Troubled	80.2% / -0.85 (.05) [c]	20.6% / 0.82 (.05) [c]	3.21 (.02) [c]	6.13 (.04) [c]	2.24 (.03) [c]

Note. GPA = Grade Point Average. Means that do not share superscripts differ at $p < .05$ on pairwise Wald tests of equality for distal outcomes across profiles.

Figure 1

BMSLSS and SEDS Item Means for the 10 CSWI Indicators Three-Profile Solution (SS = Standard Score, M = 100, SD =15)



Online Supplements

Towards an Enhanced Understanding of the Dual Factor Model of Mental Health

UC SANTA BARBARA School Mental Health COLLABORATIVE

Table SI 1. Original Greenspoon and Saklofske (2001) Dual Factor Model Study

Study	Year	Country	Sample N	Wellness Dimension	Wellness Cut-Points	Symptom Dimension	Symptom Cut-Points	**G&S** *Well-adjusted* **DFM** Complete Mental Health	**G&S** *Distressed* **DFM** Troubled	**G&S** *Dissatisfied Internalizing* **DFM** Symptomatic but content	**G&S** *Externally Maladjusted Externalizing* **DFM** Symptomatic but content
Greenspoon & Saklofske Survey 341 items Two 75-minute sessions	2001	Canada Grades 3 = 6 4 = 199 5 = 195 6 = 10 *M* age = 10.5 50% Male	Total Sample 410 **Analysis 1** Internalizing only 237 **Analysis 2** Externalizing only 162 11 Cases excluded from both analyses	**Brief Multidimensional Student Life Satisfaction Scale (BMSLSS)** No time referent	Sample Gender *T*-values Low = 1-40% High = 60-100% 41-59% (excluded)	Analysis 1 **BASC Self-Report Personality (SRP-C)** Internalizing Composite Past 6 months Analysis 2 **BASC Teacher Report Form (TRF)** Externalizing Composite Past 2 months	Analysis 1 **INT SRP-C Norm** Low = 1-40% High = 60-100% 41-59% (excluded) Analysis 2 **EXT TRF Norm** Low = 1-35% High = 66-100% 36-65% (excluded)	43% 33%	44% 40%	13% —	— 27%

Greenspoon, P. J., & Saklofske, D. H. (2001). Toward an integration of subjective well-being and psychopathology. *Social Indicators Research*, *54*(1), 81–108. https://doi.org/10.1023/A:1007219227

Table SI 2. Studies Involving Secondary School Student Samples Using the Student Life Satisfaction Scale to Measure the Dual Factor Model Wellness Dimension

Study Information				**Wellness Dimension**		**Symptom Dimension**		Complete Mental Health	Vulnerable	Symptomatic but Content	Troubled
Study	**Year**	**Country**	**Sample N**	**Wellness Indicators**	**Wellness Cut-Points**	**Symptom Indicators**	**Symptom Cut-Points**	**CMH**	**Vulnerable**	**SBC**	**Troubled**
Suldo et al.	2008	USA Ages 14-18	349 9% African American 60% White	**Student Life Satisfaction Scale (SLSS)** No time referent **Positive and Negative Affect Scale (PANAS)** Past 2 weeks	Sample values Well-Being composite (*z* SLSS + *z* PANAS-P) – (*z* PANAS-N) Low = *z* ≤ 30% High = *z* >30%	**Youth Self-Report** Internalizing norm Past 6 months **Teacher Report Form** Externalizing norm Past 2 months	Either/both Low = INT *T* < +1*SD* High = INT *T* ≥ +1*SD* Low = EXT *T* < +1 *SD* High = EXT *T* ≥ +1 *SD*	57%	13%	13%	17%
Antaramian et al.	2010	USA Grades 6-8	764 64% African American 2% White	**Student Life Satisfaction Scale (SLSS)** No time referent **Positive and Negative Affect Scale (PANAS)** Past 2 weeks	Sample values Well-Being composite (*z* SLSS + *z* PANAS-P) – (*z* PANAS-N) Low = *T* ≤ 40 High = *T* > 40	**Self-Report Coping Scale** Internalizing sample *T*-value Externalizing sample *T*-value No time referent	Either/both Low = INT *T* ≤ 59 High = INT *T* ≥ 60 Low = EXT *T* ≤ 59 High = EXT *T* ≥ 60	67%	8%	17%	8%

Study Information				Wellness Dimension		Symptom Dimension		Complete Mental Health	Vulnerable	Symptomatic but Content	Troubled
Study	**Year**	**Country**	**Sample N**	**Wellness Indicators**	**Wellness Cut-Points**	**Symptom Indicators**	**Symptom Cut-Points**	**CMH**	**Vulnerable**	**SBC**	**Troubled**
Kelly et al.	2012	USA Grades 7-8	T1:730 T2: + 5 months 27% African American 60% White	**Student Life Satisfaction Scale (SLSS)** No time referent **Positive and Negative Affect Scale (PANAS)** Past 2 weeks	Sample values Well-Being Composite Low = $T < 40$ High = $T \geq 40$ (z SLSS + z PANAS-P) – (z PANAS-N)	**Self-Report Coping Scale** Internalizing sample *T*-value Externalizing sample *T*-value No time referent	Either/both Low = INT $T \leq 59$ High = INT $T \geq 60$ Low = EXT $T \leq 59$ High = EXT $T \geq 60$	T1:64% T2:68% T1/T2 85%	T1:8% T2:9% Stability 29%	T3:20% T4:16% T1/T2 42%	T5:8% T6:7% Stability 47%
Lyons et al.	2012	USA Grades 7-8	990 58% African American 35% White	**Student Life Satisfaction Scale (SLSS)** No time referent **Positive and Negative Affect Scale (PANAS)** Past 2 weeks	Sample values Well-Being composite (z SLSS + z PANAS-P) – (z PANAS-N) Low = $z \leq -1SD$ High = $z > -1SD$	**Youth Self-Report** Internalizing norm Externalizing norm Past 6 months	Either/both Low = INT $T < +1SD$ High = INT $T \geq +1SD$ Low = EXT $T < +1\ SD$ High = EXT $T \geq +1\ SD$	64%	7%	9%	20%
Lyons et al.	2013	USA Grades 7-8	T1:808 T2 + 5 months Same sample Lyons et al. (2012)	**Student Life Satisfaction Scale (SLSS)** No time referent **Positive and Negative Affect Scale (PANAS)** Past 2 weeks	Sample values Well-Being Composite Low = $z < -1SD$ High = $z \geq -1SD$ (z SLSS + z PANAS-P) – (z PANAS-N)	**Self-Report Coping Scale** Internalizing sample values Externalizing sample values No time referent	Either/both Low = INT $T < +1SD$ High = INT $T \geq +1SD$ Low = EXT $T < +1\ SD$ High = EXT $T \geq +1\ SD$	57%	13%	13%	17%
Suldo et al.	2016	USA Ages 1 4-18	500 24% Hispanic 44% White	**Student Life Satisfaction Scale (SLSS)** No time referent **Positive and Negative Affect Scale (PANAS)** Past 2 weeks	Sample values Well-Being Composite Low = $z \leq$ 26.3% High = $z \geq$ 26.4% (z SLSS + z PANAS-P) – (z PANAS-N)	**Self-Report Personality-Adolescent** Internalizing norm Past 6 months **Teacher Rating Form** Externalizing norm Past 2 months	Age-Gender Either/both Low = INT $T \leq 59$ (73.6%) High = INT $T \geq 60$ (26.4%) Low = EXT $T \leq 59$ High = EXT $T \geq 60$	62%	11%	11%	15%
DiLeo et al.	2022	USA Ages 14-18	T1:533 T2:499 +8 mo. T3:328 +12 mo. 21% Hispanic 46% White	**Student Life Satisfaction Scale (SLSS)** No time referent **Positive and Negative Affect Scale (PANAS)** Past 2 weeks	Sample values Well-Being Composite SLSS + PANAS-C Composite (z SLSS + z PANAS-P) – (z PANAS-N)	**Behavior Problem Monitor-Youth** Sample values Past 6 months	Gender Either/both Low Male = ≤ 4 (T <65) High Male = ≥ 5 (T > 65) Low Female = ≤ 6 (T < 65) High Female = ≥ 7 (T >65)	T1:63% T2:62% T3:52%	T1:9% T2:11% T3:11%	T1:9% T2:11% T3:11%	T1:18% T2:16% Y3:25%

Table SI 3. Dual Factor Cut-point Criteria Studies Using the Other Scales to Measure the Mental Health Positive Dimension

Study Information				Wellness Dimension		Symptom Dimension		Complete Mental Health	Vulnerable	Symptomatic but Content	Troubled
Study	**Year**	**Country**	**Sample N**	**Wellness Dimension**	**Wellness Cut-Points**	**Symptom Dimension**	**Distress Cut-Points**	**CMH**	**Vulnerable**	**SBC**	**Troubled**
Xiong et al.	2017	China	T1 531 T2 531 T1/2 +4 mo. Grades 7-12	**Satisfaction with Life Scale** (SWLS) No time referent	Sample Values (*z* SWLS + *z* PANAS-P) – (*z* PANAS-N) Low = *z* < 29% High/Average = *z* ≥ 30%	**Youth Self-Report** Internalizing norm Past 6 months **Teacher Report Form** norm Externalizing norm Past 2 months	Either/both INT ≤ 66 = low INT ≥ 67 = high EXT T ≤ 59 = low EXT T ≥ 60 = high	T1 61% T2 62% T1/2 85%	19% 21% stability 44%	9% 9% T1/2 39%	11% 9% stability 35%
Grych et al.	2020	USA	466 Ages 12-17	**Satisfaction with Life Scale** (SWLS) No time referent	Sample Values Low = 1-41% High = 42-100%	**Trauma Symptom Checklist -Youth**	Sample values Low ≤ 24 = 1-62% High ≥ 25 = 63-100%	44%	19%	17%	20%
Gonzalez et al.	2023	Spain	315 Ages 12-17	**Satisfaction with Life Scale** (SWLS) No time referent **PANAS-P** Past 2 weeks	Well-Being Sample Composite (40 items) Low = 1-30% High = 60-100% 31-59% (excluded)	**Revised Anxiety and Depression Scale for Children** No time referent	Psychopathology Sample Composite (15 items) Low = 1-30% High = 60-100% 31-59% (excluded)	31%	17%	22%	30%
Hermann et al.	2024	Sweden Life Health of Youth Study	1,833 Ages 12-17	**Mental Health Continuum–Short Form (MHC-SF)** Past month	MHC-SF Criterion algorithm Flourishing Moderate/Languishing	**Strengths & Difficulties** UK norm comparison	Low = Raw values ≤ 19 High = Raw values ≥ 20	39%	48%	3%	16%
King et al.	2021	Canada HSBC Study	21,993 Grades 6-10	**Cantril Ladder Item** **Positive Affect (PA)** **Negative Affect (NA)** No time referent	Sample values Low = *T* ≤ 39 High = *T* ≥ 40 (*z*-values Cantril + z PA) – (*z* NA)	**Health Behaviors in School-Age Children Study** Sample values Internalizing Externalizing	Sample age-gender values Low = *T* ≤ 59 High = *T* ≥ 60	68%	9% Asymptomatic yet discontent	18%	9%
Renshaw et al.	2024	USA HSBC Study	5,959 Grades 5-10	***Psychological Well-Being and Distress Screen (PWBDS)*** Well-Being items Last week	Sample values Low = < -1*SD* High/Average = ≥ -1*SD*	***5 PWBDS Distress Items*** 2 items last two weeks 3 items last six months	Sample values Low/Average = *z* <1 *SD* High = *z* ≥1 *SD*	71%	11%	13%	5%
Jefferies et al.	2023	England UK HeadStart Study	30,841 Ages 11-14	**Short Warwick-Edinburgh Mental Well-Being Scale** Last 2 weeks	Sample values Low = 7-20 (1-24%) High = 21–35 (25-100%)	**Strengths & Difficulties** Emotional symptoms	Sample values Minimal = 0-4 (1-58%) Elevated = 5-10 (59-100%)	51%	25%	8%	16%

Dual Factor Cut-point Classification Criteria Studies

References

Antaramian, S. P., Huebner, E. S., Hills, K. J., & Valois, R. F. (2010). A dual-factor model of mental health: Toward a more comprehensive understanding of youth functioning. *American Journal of Orthopsychiatry, 80*(4), 462–472. https://doi.org/10.1111/j.1939-0025.2010.01049.x

DiLeo, L. L., Suldo, S. M., Ferron, J. M., & Shaunessy-Dedrick, E. (2022). Three-wave longitudinal study of a dual-factor model: Mental health status and academic outcomes for high school students in academically accelerated curricula. *School Mental Health, 14*(3), 514. https://doi.org/10.1007/s12310-021-09497-9

González, M., Correa, C., Ruíz, S., & Barroso, E. (2023). El Modelo de Factor Dual de Salud Mental en adolescentes: Relevancia de los factores intrapersonales y contextuales de protección y riesgo [The Dual-Factor Model of Mental Health in Adolescents: Relevance of both intrapersonal and contextual protective and risk factors]. *Psicología y Salud, 33*(2), 487–498. https://doi.org/10.25009/pys.v33i2.2830

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, 90*(4), 458–467. https://doi.org/10.1037/ort0000449

Hermann, V., Söderqvist, F., Karlsson, A., Sarkadi, A., & Durbeej, N. (2024). Mental health status according to the dual-factor model in Swedish adolescents: A cross-sectional study highlighting associations with stress, resilience, social status, and gender. *PLoS ONE, 19*(3), 22. https://doi.org/10.1371/journal.pone.0299225

Jefferies, P., Fritz, J., Deighton, J., & Ungar, M. (2023). Analysis of protective factors in schoolchildren in England using the dual-factor model of mental health. *Research on Child and Adolescent Psychopathology, 51*(7), 907-920. https://doi.org/10.1007/s10802-023-01038-z

Kelly, R. M., Hills, K. J., Huebner, E. S., & McQuillin, S. D. (2012). The longitudinal stability and dynamics of group membership in the dual-factor model of mental health: Psychosocial predictors of mental health. *Canadian Journal of School Psychology, 27*(4), 337–355. https://doi.org/10.1177/0829573512458505

King, N., Davison, C. M., Pickett, W. (2021). Development of a dual-factor measure of adolescent mental health: An analysis of cross-sectional data from the 2014 Canadian Health Behaviour in School-aged Children (HBSC) study *BMJ Open, 11,* e041489. http://doi.org/10.1136/bmjopen-2020-041489

Lyons, M. D., Huebner, E. S., & Hills, K. J. (2013). The dual-factor model of mental health: A short-term longitudinal study of school-related outcomes. *Social Indicators Research, 114*(2), 549–565. https://doi.org/10.1007/s11205-012-0161-2

Lyons, M. D., Huebner, E. S., Hills, K. J., & Shinkareva, S. V. (2013). The dual-factor model of mental health: Further study of the determinants of group differences. *Canadian Journal of School Psychology, 27*(2), 183–196. https://doi.org/10.1177/0829573512443669

Magalhães, E., & Calheiros, M. M. (2017). A dual-factor model of mental health and social support: Evidence with adolescents in residential care. *Children and Youth Services Review, 79*, 442–449. https://doi.org/10.1016/j.childyouth.2017.06.041

Renshaw, T. L., Bolognino, S. J., & Clark, K. N. (2024). Exploring a dual-factor mental health screening model with children in grades 5–10. *School Psychology,* https://doi.org/10.1037/spq0000669

Suldo, S. M., & Shaffer, E. J. (2008). Looking beyond psychopathology: The dual-factor model of mental health in youth. *School Psychology Review, 37*(1), 52–68. https://www.proquest.com/scholarly-journals/looking-beyond-psychopathology-dual-factor-model/docview/622251776/se-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/SPR45-4.434-457

Xiong, J., Qin, Y., Gao, M., & Hai, M. (2017). Longitudinal study of a dual-factor model of mental health in Chinese youth. *School Psychology International, 38*(3), 287–303. https://doi.org/10.1177/0143034317689970

Table SI 4. Dual Factor Model Studies Using Latent Profile Analysis

Study Information				Latent Profile Analysis Bidimensional Variables				N	Standard Dual Factor Model Groups				Unique LPA Labeled Classes		
									Complete Mental Health	Symptomatic but Content	Vulnerable	Troubled	Good Mental Health	Moderate Mental Health	Moderate Troubled
Study	**Year**	**Country**	**Sample N**	**Wellness Dimension**	**Wellness Indicators**	**Symptom Dimension**	**Symptom Indicators**	**classes**	**CMH**	**SBC**	**Vulnerable**	**Troubled**	**GMH**	**Mod MH**	**Mod Trou**
Moore et al.	2019	USA Latent Transition Analysis	Cohort 1: 497 Grades 9-11 Cohort 2: 466 Grades 10-12	**Social Emotional Health Survey-Secondary** No time referent	Raw values Belief in Self Belief in Others Emotional Competence Engaged Living	**Strengths & Difficulties Questionnaire** 6 months	Raw values Internal External	4	9:24% 10:25% 11:21% 12:37%	9:20% 10:19% 11:29% 12:21%	— — — —	9:10% 10:7% 11:6% 12:8%	— — — —	9: 47% 10:49% 11:44% 12:34%	— — — —
Zhou et al.	2020	China	T1:1009 Grades 7-9 *M* age 13 T2:894 +6 months T3:654 +6 months	**Brief Multidimensional Life Satisfaction Scale** (BMLSS) No time referent **Rosenberg Self-Esteem Scale** No time referent	Raw values BMLSS Rosenberg	**Depression Self-Rating Scale** No time referent **Screen Child Anxiety Related Emotional Disorders** No time referent	Raw values Depression Anxiety	3	T1:51% T2:40% T3:37%	—	T1:40% T2:47% T3:49%	T1:8% T2:13% T3:14%	—	—	—
Clark & Malecki	2022	USA	404 Female 55% Grades 6-8	**Student Life Satisfaction Scale** (SLSS) No time referent **Positive and Negative Affect Scale** Past 2 weeks	Sample *z*-values SLSS PANAS-P + PANAS-N [reversed])	**Youth Self-Report Form** Past 6 months	Sample *z*-values Internal External	3	55%	34%	—	11%	—	—	—
Clark & Malecki	2024	USA	365 Same sample as Clark & Malecki (2022) Grades 6-8	**Student Life Satisfaction Scale** (SLSS) No time referent **Positive and Negative Affect Scale** Past 2 weeks	LPA *z*-values SLLS (PANAS-P + PANAS-N reversed) Cut-point (CP) *z*-value (PANAS-P + PANAS-N reversed) ≤ -1 SD Low >-1 SD high	**Youth Self-Report Form** Past 6 months	Sample *z*-values LPA Internal External CP Either/or Internal External Low < +1SD High ≥ +1 SD	4	CP:67% LPA:54% Match 76%	CP:14% LPA:35% Match 75%	CP:6% LPA — 91% of CP vulnerable cases were in the LPA SBC class	CS:13% LPA:12% Match 78%	—	—	—

Study Information				Latent Profile Analysis Bidimensional Variables				N	Standard Dual Factor Model Groups				Unique LPA Labeled Classes		
									Complete Mental Health	Symptomatic but Content	Vulnerable	Troubled	Good Mental Health	Moderate Mental Health	Moderate Troubled
Study	**Year**	**Country**	**Sample N**	**Wellness Dimension**	**Wellness Indicators**	**Symptom Dimension**	**Symptom Indicators**	**classes**	**CMH**	**SBC**	**Vulnerable**	**Troubled**	**GMH**	**Mod MH**	**Mod Trou**
Zhang et al.	2024	China	T1 484 T2 + 6 mo. T3 +6 mo. Ages 12-16	**Satisfaction with Life Scale** (SWLS) No time referent	Sample *z*-value SWLS	**Depression Anxiety Stress Scale-21** Past week **Aggression Questionnaire** No time referent	Sample *z*-values Depression Anxiety Aggression	**3**	T1:62% T2:69% T3:68%	—	—	T1:7% T2:3% T3:6%	—	T1:31% T2:28% T3:27%	—
Jiang et al.	2023	China	2277 Male 62% First year college	**Satisfaction with Life Scale** (SWLS) No time referent **Positive Affect Scale** (PAS) Past week	Raw values SWLS PAS	**Self-Rating Depression Scale** Several days **Negative Affect Scale** (NAS) Past week	Raw Values Depression NAS	**3**	48%	—	44%	8%	—	—	—
Sechague Monroy et al.	2024	Australia Academic outcomes	3587 Yr 1: Grade 6 Outcomes in Grades 7-9	**Satisfaction with Life Scale**-Child No time referent **EPOCH Measurement of Adolescent Well-Being** item I am happy with my life No time referent	Raw Values Satisfaction Optimism Happiness	**Middle Years Development**	Raw Values Sadness Worries	**6**	30%	19%	6%	8%	—	18%	19%
Gregory et al.	2024	Australia	75,757 Ages 8-18	**Satisfaction with Life Scale**-Child No time referent **EPOCH Measurement of Adolescent Well-Being** item I am happy with my life No time referent	Raw Values Life Satisfaction Optimism Happiness	**Seattle Personality Questionnaire** No time referent **Worries** I feel unhappy a lot of the time	Raw Values Sadness Worries	**5**	23%	9%	—	8%	33%	27%	—
Maurer et al.	2025	Sweden During COVID	846 *M* age18 66% Female	**EPOCH Measurement of Adolescent Well-Being** No time referent	Sample *z*-values Engagement Perseverance Optimism Connectedness Happiness	**Depression Anxiety and Stress Scale–21** Past week	Sample *z*-values Depression Anxiety Stress	**5**	43%	5% "Symptomatic but managing"	10%	4%		38%	—

Study Information				Latent Profile Analysis Bidimensional Variables				N	Standard Dual Factor Model Groups				Unique LPA Labeled Classes		
									Complete Mental Health	Symptomatic but Content	Vulnerable	Troubled	Good Mental Health	Moderate Mental Health	Moderate Troubled
Study	**Year**	**Country**	**Sample N**	**Wellness Dimension**	**Wellness Indicators**	**Symptom Dimension**	**Symptom Indicators**	**classes**	**CMH**	**SBC**	**Vulnerable**	**Troubled**	**GMH**	**Mod MH**	**Mod Trou**
Hernández Torran & Ibrayeva	2025	Kazakhstan	2262 *M* age 20 years	**Mental Health Continuum-Short Form** (MHC-SF) Past month **Satisfaction with Life Scale (**SWLS) No time referent	Raw Values MHC-SF Emotional Social Psychological SWLS	**Patient Health Questionnaire-4** Past 2 weeks	Raw values Anxiety Depression Total Score	4	29%	20%	21%	21%	—	—	—
Chen et al.	2025	China	575 *M* Age 18 Year 1 college	**Mental Health Continuum-Short Form** Past month	Raw values MHC-SF Emotional Social Psychological	**Depression, Anxiety, Stress Scale-21** Past week	Raw values Depression Anxiety Stress	4	46% "flourishing"	10% "Content but symptoms"	—	17% "Symptoms dominated but content"	—	27%	—
Lim & Yang	2025	USA	206 10-19 Yrs. Chinese American	**Social Emotional Health Survey-Secondary** No time referent	Sample z-values Peer Support Family Support School Support Optimism Gratitude Zest	**Youth Internalizing Problem Screener Youth Externalizing Problem Screener** Past month	Sample z-values Depression Anxiety Conduct/ Oppositional Hyperactivity/ Impulsivity	4	42%	20%	29%	8%	—	—	—

Dual Factor Latent Profile Analysis Classification Studies

References

Chen, R., Gao, X., Zhang, Z. et al. (2025). What predicts mental health profiles in first-generation college freshmen? The role of proactive personality and university environment. *BMC Psychology, 13*, 166. https://doi.org/10.1186/s40359-025-02498-2

Clark, K. N., & Malecki, C. K. (2022). Adolescent mental health profiles through a latent dual-factor approach. *Journal of School Psychology, 91*, 112–128. https://doi.org/10.1016/j.jsp.2022.01.003

Clark, K. N., Blyth, G., Plant, M., Wilson, K., & Malecki, C. K. (2024). Dual-factor mental health in adolescence: Comparing classification methods. *Journal of School Psychology, 107*, 101391. https://doi.org/10.1016/j.jsp.2024.101391

Gregory, T., Monroy, N. S., Grace, B., Finlay-Jones, A., Brushe, M., Sincovich, A., Heritage, B., Boulton, Z., & Brinkman, S. A. (2024). Mental health profiles and academic achievement in Australian school students. *Journal of School Psychology, 103,* 101291. https://doi.org/10.1016/j.jsp.2024.101291

Hernández-Torrano, D.,& Ibrayeva, L. (2025). Who feels good at university? Exploring the prevalence, profiles, and determinants of mental health in higher education students using a person-centered approach. *Asia-Pacific Education Research, 34,* 93–107. https://doi.org/10.1007/s40299-024-00839-0

Jiang, Y., Ding, C., & Shen, B. (2023). Latent profile analysis of mental health among Chinese university students: Evidence for the dual-factor model. *Healthcare*, *11*(20), 2719. https://doi.org/10.3390/healthcare11202719

Maurer, M. M., Hoff, E., & Daukantaitė, D. (2025). Mental health profiles among Swedish high school students: Relationships to environmental sensitivity and coping self-efficacy. *Journal of Happiness Studies, 26*, 37. https://doi.org/10.1007/

Moore, S. A., Carter, D., Kim, E. K., Furlong, M. J., Nylund-Gibson, K., & Dowdy, E. (2024). Adolescents' Covitality patterns: Relations with student demographic characteristics and proximal academic and mental health outcomes. *School Mental Health, 16,* 550–565 (2024). https://doi.org/10.1007/s12310-024-09663-9

Moore, S. A., Dowdy, E., Nylund-Gibson, K., & Furlong, M. J. (2019). An empirical approach to complete mental health classification in adolescents. *School Mental Health, 11*(3), 438–453. https://doi.org/10.1007/s12310-019-09311-7

Moore, S. A., Dowdy, E., Nylund-Gibson, K., & Furlong, M. J. (2019). 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

Sechague Monroy, N., Brushe, M., Sincovich, A., Boulton, Z., & Gregory, T. (2024). Associations between mental health profiles and later school outcomes. *Australian Journal of Education, 68*(3), 199–223. https://doi.org/10.1177/00049441241278411 (Original work published 2024)

Zhang, Q., Tu, Y., Yao, S., Zhang, Q., Liu, J., & Peng, Q. (2025). Impact of childhood maltreatment on adolescents' mental health–A longitudinal study based on the dual-factor model. *BMC Psychology, 13*, 95. https://doi.org/10.1186/s40359-025-02398-5

Zhou, J., Jiang, S., Zhu, X., Huebner, E. S., & Tian, L. (2020). Profiles and transitions of dual-factor mental health among Chinese early adolescents: The predictive roles of perceived psychological need satisfaction and stress in school. *Journal of Youth and Adolescence, 49*(10),2090–2108. https://doi.org/10.1007/s10964-020-01253-7

Table SI 5. Main Study Measures and Items

Brief Multidimensional Life Satisfaction Scale (BMSLSS)

Generally, how satisfied are you with your life?

I would describe my satisfaction with my FAMILY life as...
I would describe my satisfaction with my FRIENDSHIPS as...
I would describe my satisfaction with my SCHOOL EXPERIENCE as...
I would describe my satisfaction with MYSELF as...
I would describe my satisfaction with my WHERE I LIVE as...

Responses: 0 = Very Dissatisfied, 1 = Moderately Dissatisfied, 2 = Mildly Dissatisfied, 3 = Mildly Satisfied, 4 = Moderately Satisfied, 5 = Very Satisfied

Social Emotional Distress Scale (SEDS)

In the past month:

It was hard for me to get excited about anything. (hard get excited)
I felt sad and down. (sad)
I had a hard time relaxing. (hard relax)
It was hard for me to cope, and I thought I would panic. (hard cope)
I was easily irritated. (irritated)

Responses: 0 = Not true of me, 1 = A little true of me, 2 = Pretty much true of me, 3 = Very true of me

School Connectedness Scale

I feel close to people at this school.
I am happy to be at this school.
I feel like I am part of this school.
The teachers at this school treat students fairly.
I feel safe in my school.

Responses: 0 = Strongly Disagree, 1 = Disagree, 2 = Neither Agree or Disagree, 3 = Agree, 4 = Strongly Agree

Table SI 6. Descriptive Statistics and Correlation Coefficients of Central Study Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Family	—														
2. Friendship	.52	—													
3. School	.45	.50	—												
4. Myself	.56	.49	.54	—											
5. Where live	.59	.47	.42	.46	—										
6. Hard relax	-.24	-.18	-.29	-.40	-.15	—									
7. Sad	-.29	-.24	-.34	-.50	-.17	.62	—								
8. Irritated	-.23	-.17	-.30	-.39	-.14	.59	.65	—							
9. Hard cope	-.28	-.20	-.28	-.44	-.17	.60	.69	.60	—						
10. Hard get excited	-.28	-.24	-.33	-.45	-.19	.57	.62	.54	.62	—					
11. Persistent depressed mood	-.28	-.22	-.32	-.44	-19	.43	.59	.45	.52	.48	—				
12. Suicidal thoughts	-.27	-.16	-.24	-.40	-.17	.30	.42	.33	.41	.36	.43	—			
13. School connectedness	.30	.36	.59	.38	.30	-.25	-.28	-.27	-.26	-.31	-.28	-.22	—		
14. Academic grade	.17	.11	.22	.15	.18	-.03	-.05	-.05	-.06	-.10	-.14	-.08	.23	—	
15. Absence	-.09	-.08	-.15	-.09	-.11	.09	.09	.10	.11	.09	.12	.06	-.14	-.22	—
N	17,660	17,602	17,570	17,600	17,598	17,839	17,782	17,706	17,789	17,793	18,018	17,985	18,921	19,570	19,705
Range	0-5	0-5	0-5	0-5	0-5	0-3	0-3	0-3	0-3	0-3	0/1	0/1	1-5	1-8	1-4
M	3.88	3.86	3.01	3.27	4.02	0.97	0.96	1.19	0.63	0.64	0.29	0.12	3.49	6.24	2.06
SD	1.28	1.20	1.38	1.53	1.20	0.99	1.03	1.10	0.96	0.93	0.46	0.32	0.78	1.76	1.13

Note all correlation ps < .001.

Table SI 7. Fit Statistics for Confirmatory Latent Profile Analysis Using Multiple Groups Framework

	LL	AIC	BIC	npar	Model Comparison	adjustedLRT
Model a: configural invariance	-490909.71	981949.41	982500.23	65	—	—
Model b: full indicator means invariant	-490922.67	981955.33	982421.41	55	2 vs. 1	-14.59
Model c: full indicator means and variances, covariances invariant	-490928.40	981946.80	982328.13	45	3 vs. 2	0.31

Note. LL = model maximum log likelihood value; AIC = Akaike information criteria; BIC = Bayesian information criteria; npar = number of free parameters estimated in the model; LRT = likelihood ratio difference test (values shown in bold indicate the model with the smallest number of free parameters that is rejected with $p < .05$).

Table SI 8. Students' Demographic Correlates for Three-Profile Solution Using Troubled Profile as Reference Group

Profile	Variable	*Logit*	*SE*	OR
1. Flourishing	American Indian/ Alaska Native	0.67	0.38	1.96
	Asian	0.13	0.09	1.14
	Black	0.25	0.15	1.29
	Latino/a/x	0.28	0.08	1.32
	Native Hawaiian/ Pacific Islander	0.70	0.51	2.02
	Mixed Race	-0.08	0.08	0.93
	Other racial/ethnic groups	0.18	0.16	1.19
	Grade	-0.05	0.02	0.95
	Male	1.08	0.06	2.93
	Other gender identity	-0.23	0.19	0.79
	Lesbian or gay	-1.46	0.15	0.23
	Bisexual	-1.43	0.09	0.24
	Other housing conditions	**-0.26***	0.12	0.77
	Parent education below college	-0.22	0.06	0.80
	English language program	0.14	0.11	1.14
2. Moderate	American Indian/ Alaska Native	-0.012	0.481	0.99
	Asian	0.16	0.10	1.18
	Black	-0.29	0.19	0.75
	Latino/a/x	0.01	0.10	1.01
	Native Hawaiian/ Pacific Islander	-0.02	0.57	0.98
	Mixed Race	**-0.24***	0.09	0.79
	Other racial/ethnic groups	0.00	0.20	1.00
	Grade	0.00	0.02	1.00
	Male	0.36	0.07	1.43
	Other gender identity	-0.70	0.24	0.50
	Lesbian or gay	-0.75	0.17	0.47
	Bisexual	-0.57	0.10	0.56
	Other housing conditions	0.07	0.13	1.07
	Parent education below college	**-0.19***	0.07	0.82
	English language program	0.06	0.13	1.06

Note. OR = Odds Ratio.

* $p < .05$.