



# Heterogeneity Among Moderate Mental Health Students on the Mental Health Continuum-Short Form (MHC-SF)

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## Abstract

Measures of positive well-being are needed to support the shift away from a deficit-based approach to mental health. This study examined one measure, the Mental Health Continuum-Short Form (MHC-SF), as a measure of positive well-being used in school-based mental health monitoring efforts. This study used latent profile analysis (LPA) to explore the mental health classifications of 10,880 California high school students' responses to MHC-SF emotional, psychological, and social well-being items. Five latent mental wellness profiles emerged, including two ordered profiles (i.e., High Well-Being and Low Well-Being) and three profiles spanning the two ordered profiles. The High Well-Being profile had the most favorable psychological adjustment, and the three moderate well-being range profiles had differentiated functioning. Informing the utility of the MHC-SF, this study also compared the MHC-SF categorical diagnostic criteria with the LPA's empirical classification approach and found the two classification approaches to be congruent. The findings provide an impetus for educators to attend to students in moderate well-being ranges and emphasize promoting positive mental well-being as an essential component of school-based mental health services.

**Keywords** MHC-SF · Latent profile analysis · School-based mental health · Mental health screening · Adolescents

## Introduction

School mental health programs are moving away from an individual deficit-based approach toward a universal preventive approach focused on positive psychological well-being in addition to psychological distress (Dowdy et al., 2015). Corresponding with this school mental health reform, Keyes (2002, 2005) introduced the dual continua model that posits mental illness and mental health as two correlated continua rather than opposite ends of a single continuum. Complete mental health consists of well-being “symptoms,” in addition to the absence of mental illnesses (Keyes, 2002, 2005). Under such a mental health paradigm, school-based

wellness programs support vulnerable students and promote all students' well-being, emphasizing their thriving and optimal potential (Kim et al., 2014). Serving this prevention and promotion vision requires a thorough conceptualization and measurement of positive psychological well-being, in addition to the measurement of psychological distress. The Mental Health Continuum-Short Form (MHC-SF) is an instrument to build upon the dual continua model and Ryff's multidimensional model of Psychology Well-Being (Keyes, 2005; Ryff & Keyes, 1995), which could be valuable in supporting this shift to a focus on positive psychological well-being. However, to date, there is limited research informing school mental health professionals about the MHC-SF's potential utility in school-based screening. In particular, empirical evidence about the validity of the current MHC-SF diagnostic approach is scant. Hence, this study aims to evaluate the MHC-SF critically as a measure of positive psychological well-being.

## Dual Continua Model Theoretical Framework

An effective school-based mental health screening identifies students who are experiencing psychological distress and

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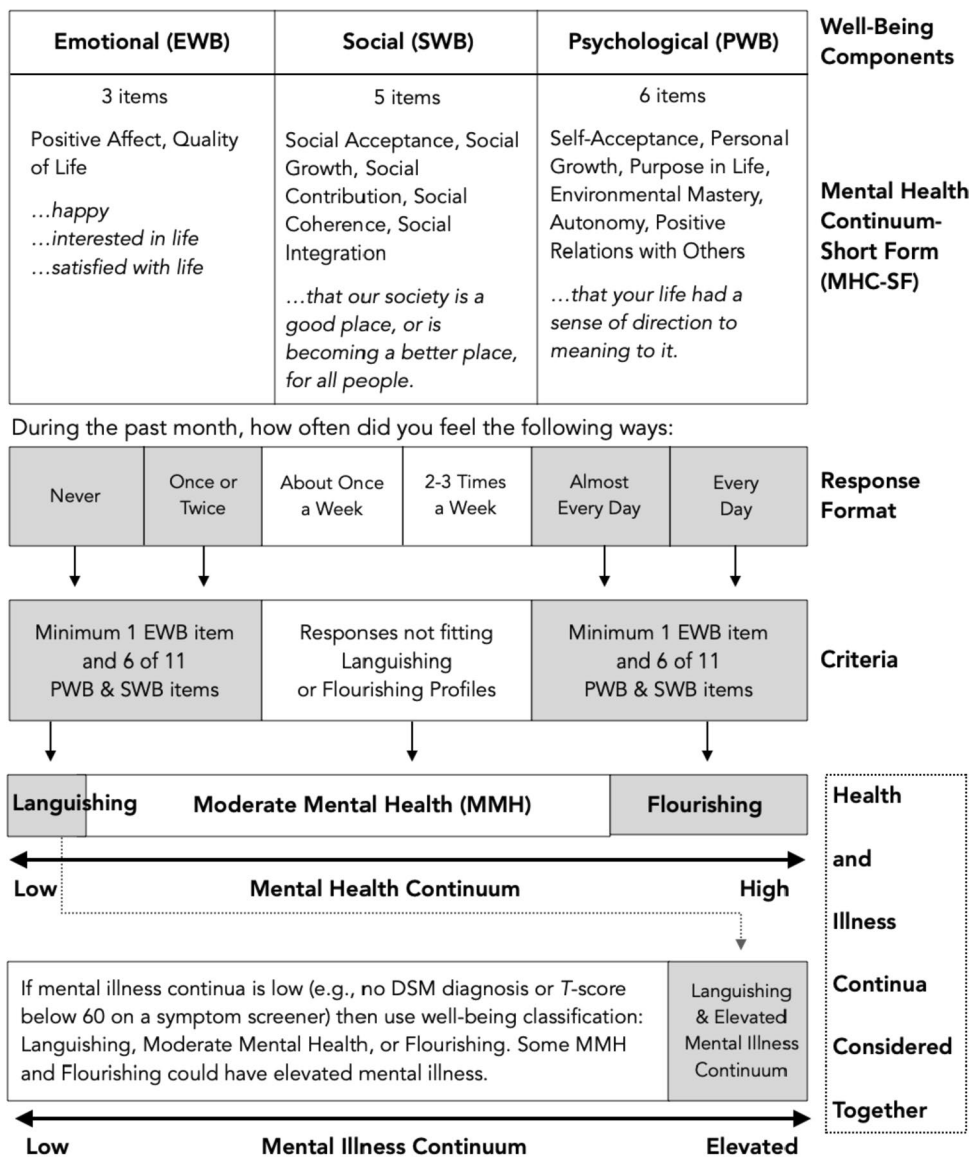
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students who may not be experiencing symptoms of distress but who are not psychologically flourishing or experiencing positive mental health. This is consistent with conceptualizations of mental health according to the dual continua model because the experience of psychological distress and positive mental health or well-being are two independent dimensions (Dowdy et al., 2015; Keyes, 2005). Within the dual continua model, as shown in Fig. 1, positive mental health is considered multidimensional, comprised of emotional, psychological, and social dimensions of subjective well-being (Keyes, 2002, 2005). Emotional well-being refers to the perception of positive affect and life satisfaction over some time. The other two aspects underscore human potential to attain positive functioning. Psychological well-being is defined by six

components (self-acceptance, personal growth, purpose in life, positive relations with others, autonomy, and environmental mastery), collectively indicating individuals’ pursuit of maximizing their potentials (Keyes, 2002). Social well-being, capturing individuals’ perception of their relationship with and engagement in society (Keyes, 1998, 2016), is represented by five components: social integration, social contribution, social coherence, social actualization, and social acceptance. An individual has positive mental health when their well-being profile suggests frequent weekly or daily experiences of positive affect and with no indications of mental distress symptoms (Keyes, 2005, 2006).

Keyes (2007) introduced the Mental Health Continuum-Short Form (MHC-SF) to measure multidimensional

**Fig. 1** Mental health continuum-short form categorical diagnostic scheme



Note. MHC-SF description, items, and scoring available at: <https://www.aacu.org/sites/default/files/MHC-SFEnglish.pdf>. The cell sizes in Mental Health Continuum (see, Keyes, 2006) and Mental Illness (see, Kessler et al., 2007) rows illustrate the proportion of adolescents reported in each classification.

well-being, differentiated from the mental illness continuum. As Keyes conceptualized, mental health can be considered a syndrome of subjective well-being symptoms, much as diagnostic criteria define mental illnesses in the Diagnostic and Statistical Manual of Mental Disorders (DSM; Keyes, 2006). Like the DSM, the MHC-SF employs clinical diagnostic criteria (Keyes, 2005), not response normative distributions, to interpret individual response patterns. The MHC-SF criteria classify individuals into Flourishing, Languishing, and Moderate Mental Health diagnostic categories. Youths are diagnosed as Flourishing or Languishing by the intensity of psychological, emotional, and social well-being symptoms they experienced during the past 30 days. Youth whose category is neither Languishing nor Flourishing fall in the Moderate Mental Health category. Figure 1 illustrates the criterion-referenced algorithm for mental health classification. The three mental health categories have demonstrated strong associations with conduct problems, suicidal behaviors, academic performance, and psychosocial functioning among US adolescents and college students (Keyes, 2005, 2006; Keyes et al., 2012). This positive mental health multidimensional framework using the MHC-SF has been validated in various countries and subgroups (e.g., age groups, gender, and clinical sample; Keyes, 2016; Guo et al., 2015; Lamers et al., 2011; Żemojtel-Piotrowska et al., 2018).

Despite its robust theoretical framework and associations with adolescents' functioning, the MHC-SF requires further research to inform school-based wellness programs, including its use as part of school-based screening and monitoring efforts. A relevant limitation of the MHC-SF is its limited empirical evidence supporting the MHC-SF category symptom thresholds with adolescents (Keyes, 2005). An investigation of the congruence of the three mental health categories classified by the diagnostic approach and adolescents' actual response profiles of well-being symptoms may help understand the application of the MHC-SF classification scheme among US adolescents.

### Application of MHC-SF in School

The MHC-SF has several potential advantages for school-based universal screening applications, particularly when considering the dual continua model's focus on psychological well-being and distress. Even though the importance of positive mental health has been emphasized, the primary applications of school-based screening and monitoring remain deficit-oriented, focusing on identifying symptoms of psychological distress experienced by only a small percentage of students (Dowdy et al., 2015). Multidimensional well-being measures, such as the MHC-SF, have a place within the universal school-based screening literature to augment deficit-based scales frequently used in schools and identify students who are not flourishing in

addition to students currently in distress. The multifaceted nature of the MHC-SF, with only 14 items, could be easily incorporated into school-based mental health screening and monitoring. Moreover, the MHC-SF offers a criterion-referenced classification to assess the "mental health" continuum. This standardized approach means students can be placed into its three broad categories (i.e., Flourishing, Languishing, and Moderate Mental Health) with 100% accuracy without reference to other peer responses and across all schools. This scale provides educators with information about positive psychosocial development for *all* students, consistent with educational approaches taking a whole child developmental perspective (Cantor et al., 2021).

The MHC-SF may provide helpful information for educators to support students in the *middle* subjective well-being zone who have been underemphasized in school mental health programs. Consistent with the focus on universal services characteristic of school mental health paradigms, schools need to help *all* children thrive (Furlong, in press; Keyes, 2005, 2006), not only the smaller percentage of students currently experiencing psychological distress. Even though students in the Moderate Mental Health group are proportionately substantial, they are overlooked in mental health prevention, and there is limited knowledge of their characteristics. In the USA, Keyes (2006) showed that 38% of adolescents were Flourishing, 56% had Moderate Mental Health, and 6% identified as Languishing. Another group of researchers examined 5399 Chinese middle and high school students' responses to the MHC-SF and found 57% were Flourishing, 37% had Moderate Mental Health, and 5% were Languishing (Guo et al., 2015). In South Korea, 12% of the Grade 10 participants fit the categorical diagnosis of Flourishing, while 13% were Languishing, and 75% had Moderate Mental Health (Lim, 2014). All these studies suggested that the Moderate Mental Health group ranged from one-third to over one-half of the youth regardless of country, comprising a considerable portion of the total student population.

Not only Languishing individuals, but individuals in the Moderate Mental Health diagnostic category are at higher risk of reporting mental illness symptoms and nonoptimal functioning than those in the Flourishing group (Keyes, 2007, 2016). In a longitudinal study of a nationally representative sample of US adults, Keyes showed that participants who stayed or moved to the Moderate Mental Health group were 3–4 times more likely to develop a mental illness than individuals in the Flourishing group. Participants who moved to or stayed as Flourishing had the lowest probability of developing mental illnesses. Promoting students' progression in the Moderate Mental Health group toward Flourishing via school mental wellness programs appears to be a promising way to reduce the number of students experiencing future mental illness (Costello et al., 2003; Keyes, 2016).

The MHC-SF is an instrument that could help identify the services that help youths in the Moderate Mental Health range transition upward on the mental wellness continuum. However, its current diagnostic approach gives little information for supporting youth who are not flourishing. The default Moderate Mental Health category has no unique response pattern criteria but is simply the category provided to students not classified as Flourishing or Languishing. Given the sizable proportion (in the 35–50% range across samples) of youths in the Moderate Mental Health category (Guo et al., 2015; Keyes, 2006), they are likely heterogeneous in their response profiles. For instance, youths placed in the Moderate Mental Health classification could have answered five of the 11 psychological and social well-being items *almost every day*, just one response out of the Flourishing category. In comparison, other students in the Moderate Mental Health category could have responded once or twice on five of the 11 psychological and social well-being items, just one less than those in the Languishing category. Nonetheless, these youths with empirically different profiles would be placed in the Moderate Mental Health group, even though their response patterns likely implicate different types and degrees of support services needed.

Understanding the heterogeneities of Moderate Mental Health youths' response profiles could assist school mental health professionals. This differentiated understanding might help identify which intervention students with Moderate Mental Health need to prevent declining toward the Languishing category and bolster them toward the Flourishing category. To date, limited research has examined the possible presence of heterogeneity among the Moderate Mental Health diagnostic category and if differentiated response patterns are associated with meaningful clinical diagnostic subcategories. An exploration of other classification methods, such as latent profile analysis (LPA), an empirical method, might provide educators and researchers an alternative perspective of mental health classification and inform how to utilize the MHC-SF in school-based mental health screening. The current study contributes to MHC-SF research applications by empirically examining response patterns through LPA. Of particular interest, employing latent profile analysis, we evaluated if students falling in the MHC-SF's moderate range on the positive mental health continuum show different response patterns on its three well-being domains (emotional, social, and psychological).

### Empirical Approach to Classify Students' Mental Health

Latent profile analysis (LPA) uses empirical algorithms to categorize individuals based on their response patterns to relevant items. The current study used the MHC-SF domain (emotional, psychosocial, and social) means as indicators to

examine adolescents' mental health profiles. Provided that the three MHC-SF subjective well-being subscales are interrelated yet distinct (Keyes, 2005), some students may experience varying levels of well-being in each dimension. LPA can potentially provide a nuanced perspective to advance an understanding of students' well-being by identifying more than the three diagnostic categories proposed by Keyes (2005). Comparing MHC-SF categories using different approaches, such as through LPA and categorical diagnostic approaches, could help educators and researchers understand emergent mental health groups using other techniques and inform applications of the two classification approaches.

### Current Study

This study aims to critically evaluate the utility of the MHC-SF for mental health screening and monitoring through exploring more detailed differentiation of the MHC-SF response profiles among US adolescents. LPA was employed to explore youth responses to the MHC-SF items across emotional, psychological, and social well-being. Considering previous MHC-SF person-centered studies (Reinhardt et al., 2020) and the theoretical assumptions of its three interrelated and distinctive mental health components (Keyes, 2005), we hypothesized that the LPA would identify Keyes' consistently low (i.e., similar to Languishing) and high (i.e., similar to Flourishing) profiles. Of interest and pertinent to the current study's contribution aims, we further hypothesized that more than three LPA classes would emerge due to the undifferentiated definition for the Moderate Mental Health classification. Subsequently, we examined the LPA profile associations with student psychological strengths and distress to assess the profiles' meaning and validity. In addition, we included psychological strengths and distress as proxies of quality of life given their robust and extensive associations with youth functioning in various aspects (e.g., substance use and academic achievement; Furlong et al., 2021; Dowdy et al., 2018). Finally, to inform educators' application of the current study's results, we evaluated the students' MHC-SF diagnostic categories' congruence with their LPA profiles. Comparing the two classification methods could help researchers and educators better understand the meaning of the empirically derived mental health profiles using the traditional MHC-SF diagnostic categories as a reference point.

### Method

#### Participants and Procedure

The sample of 10,880 participants attended one of 17 high schools located in nine counties randomly selected from

California public high schools. Students were enrolled in Grade 9 (33.6%), Grade 10 (20.9%), Grade 11 (28.8%), or Grade 12 (16.6%). The number of respondents in each school ranged from 216 to 1355. Forty-three percent of enrolled students completed the survey. The ethnic identification of the participants included: 39.2% White, 37.1% Mixed Race, 4% Black, 11.6% Asian, 2.2% Native Hawaiian/Pacific Islander, 5.9% Alaskan/Native American, and 7.2% did not answer. In addition, there were 48.2% Latinx students. The sample included 37.8% males and 40.3% females, with 1.2% missing responses. For two school districts, information about students' binary gender identity was not included, accounting for 21.9% of the sample. Table 1 shows the demographic information of participants in the present study.

The CHKS is California's biennial statewide survey that anonymously asks about student risk behaviors and resilience factors. A supplementary module included the MHC-SF and other psychological health measures. The sample in this study responded to the survey between October 2017 and June 2019. The proctors' survey administration was standardized. Designated school personnel with experience administering the CHKS followed a script that reminded students that the survey was anonymous and voluntary. Students completed the survey during school hours after receiving their assent. Parents provided passive consent following the standard procedures (see <http://chks.wested.org/administer/instructions>). The Human Subjects Committee at the authors' university has confirmed that no ethical approval is required.

**Table 1** Descriptive statistics of indicators and covariates

Indicators	<i>M</i>	<i>SD</i>
<i>Latent profile analysis indicators</i>		
Emotional well-being	4.39	1.43
Social well-being	3.61	1.54
Psychological well-being	4.19	1.46
<i>Distal outcomes</i>		
Psychological strengths	2.86	0.52
Psychological distress	2.08	0.85
<i>Demographic variables</i>		
FRMP	Percentage	
Students of color	47.7%	
Female	56.4%	
No response gender item	40.3%	
Sexual minorities	21.9%	
	12.2%	

FRMP free and reduced meal program

## Measures

### Demographic Covariates

Students' socioeconomic circumstances, ethnic identity, gender identity, and sexual orientation were included in the analyses because the effects of these individual characteristics on adolescents' social emotional strengths and psychological distress have been reported in the literature (e.g., Heintz et al., 2019; Kuo et al., 2020; Ueno, 2005). Students' socioeconomic circumstances were indicated by participation in the school free and reduced-price meal program using three categories (*yes, no, or don't know*). Students responded to a gender identity item using a binary option (*female or male*) with male as the reference group. Students reported six ethnic identities (*American Indian, Asian, Black or African American, Native Hawaiian or Pacific Islander, White, or Mixed Race*), categorized into Students of Color and White for the analysis with White as the reference group. Finally, students were asked about their preferred sexual orientation using six categories (*straight, gay or lesbian, bisexual, I am not sure yet, something else, or decline to respond*). Students who selected options other than *straight* were coded as *sexual minorities*, with students who identified as *straight* as the reference group.

### Profile Indicators: Mental Health Continuum-Short Form (MHC-SF)

The Mental Health Continuum-Short Form (MHC-SF; Keyes, 2005) measures emotional, psychological, and social well-being. Adapted from the 40-item MHC-Long Form (MHC-LF; Keyes, 2002, 2005), the MHC-SF includes the 14 MHC-LF items that best represented each construct under three dimensions of well-being: *emotional* (EWB; i.e., life satisfaction, positive affect, negative affect), *psychological* (PWB; i.e., autonomy, environmental mastery, personal growth, positive relations with others, purpose in life, and self-acceptance), and *social well-being* (SWB; i.e., social integration, social acceptance, social contribution, social actualization, and social coherence; Keyes, 2005). Example items are: *How often did you feel satisfied with life?* (EWB), *How often did you feel that the way our society works made sense to you?* (SWB), and *How often did you feel confident to think or express your own ideas and opinions?* (PSW). The MHC-SF asks students to self-report the frequency of past-month experiences on a six-point response scale (1 = *never*, 2 = *once or twice*, 3 = *about once a week*, 4 = *two or three times a week*, 5 = *almost every day*, and 6 = *every day*). The scale

has shown acceptable internal consistency and discriminant reliability among adolescents and adults across countries (e.g., Joshanloo, 2019; Söderqvist & Larm, 2021; Zemojtel-Piotrowska et al., 2018). The Omega values of the internal reliability of EWB, SWB, and PWB subscales for the present sample were 0.88, 0.90, and 0.91, respectively.

### Distal Outcomes: Psychological Strengths

Students' psychological strengths were assessed by the Social Emotional Health Survey-Secondary (SEHS-S) with 36 items (Furlong et al., 2014). The SEHS-S assesses a third-order meta-construct, named Covitality, four second-order constructs, and 12 first-order constructs. Each second-order social emotional strength includes three first-order subscales with three items in each (Furlong et al., 2014). The four second-order and 12 first-order constructs are *Belief in Self* (self-efficacy, self-awareness, persistence), *Belief in Others* (school support, peer support, family support), *Engaged Living* (optimism, gratitude, zest), and *Emotional Competence* (emotional regulation, empathy, self-control). Example items are: *I feel bad when someone gets their feelings hurt* and *I think before I act*. The SEHS-S has been examined in representative samples of middle and high school students in the USA, showing high validity and internal reliability estimates (Furlong et al., 2014, 2021; You et al., 2014). The latent meta-construct, Covitality, representing an overall level of social emotional competencies, is correlated with students' grade-point-average (You et al., 2014), perceived school safety, and substance use among US high school students (Furlong et al., 2014). To better understand how the emerging mental health profiles relate to psychological strengths, this study used the Covitality score (i.e., a mean score of the four second-order constructs) as a distal outcome. The measure uses a four-point response scale (1 = *not at all true*, 2 = *a little true*, 3 = *pretty much true*, and 4 = *very much true*). Higher Covitality scores represent higher overall psychological strength. The Omega value of the internal reliability of the scale for the current study sample was 0.85.

### Distal Outcomes: Psychological Distress

The Social Emotional Distress Scale-Secondary (SEDS-S) measured psychological distress. An example item is *Over the past month, I felt sad and down*. Students responded to a four-point response scale (1 = *not at all true*, 2 = *a little true*, 3 = *pretty much true*, and 4 = *very much true*). Higher scores indicate more frequent experiences of emotional distress in a month. This one-factor scale demonstrated acceptable convergent and discriminant validity as shown by its strong and positive association with anxiety and depression symptoms and moderate and negative relation with life satisfaction

among US adolescents (Dowdy et al., 2018). Prior studies also showed high internal reliability among US high school students (e.g., Dowdy et al., 2018). In the current sample, the Omega value internal reliability was 0.92.

### Preliminary Analysis on Missing Data

Since we did not have information about gender identity for approximately one-fifth of the participants, this group of students was included in the analysis and controlled by the covariate (*no gender identity information*) to account for its potential impact on distal outcomes. In addition, a sensitivity analysis ensured no sample bias on class enumeration between the samples with and without this group of students.

The rate of missing responses to the items measuring the profile indicators and distal outcomes ranged from 0.2 to 4.9%. Regarding the missingness on the demographic variables, the missing rates were all under 5.0%, except for sexual orientation with 14.7% missing responses and free and reduced-price meal programs with 9.2% missing responses. Thus, the proportions of the missingness were at an acceptable range (Dong & Peng, 2013). For the items with relatively high missing rates, the results of independent *t*-tests indicated that missingness on sexual orientation and free and reduced-price meal program did not have a significant influence on responses to the distal outcomes. These results implied that there was no systematic difference in the missing responses. Hence, all models were estimated via maximum likelihood estimation with robust standard errors (MLR) using 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

Analyses were conducted on Mplus 8.4 (Muthén & Muthén, 2017) using maximum likelihood estimation with robust standard errors (MLR). The distributions of the three profile indicators were negatively skewed. Given the nested nature of the sample, the variables interclass correlations (ICC) were examined. The ICCs of the three mental health dimensions and two distal outcomes ranged from 0.014 and 0.009, suggesting that variables at the student level mostly accounted for the variances of these variables. The analysis consisted of three steps: (a) class enumeration, (b) estimating profiles' relations with distal outcomes, and (c) comparing mental health classification congruence between categorical diagnostic approach and latent profile analysis. In step 1, using the three composite scores from each dimension of the MHC-SF, 1-to 8-class LPA models were estimated. Provided that latent profiles can vary by their indicator means,

variances, and covariances, we analyzed four model structures for each number of latent profiles (Masyn, 2013):

1. Model 1: indicator variances were freely estimated but constrained to be equal across classes, with no within-class indicator covariances.
2. Model 2: indicator variances were estimated freely, and no within-class indicator covariance was specified.
3. Model 3: indicator variances were constrained to be equal across classes, and within-class indicator covariances were specified.
4. Model 4: indicator variances were constrained to be equal across classes, and indicator covariances for the overall model were specified.

The final model was selected based on the relative fit indices of the plausible competing models along with conceptual merits and profiles' meaning (Masyn, 2013).

Given no consensus on latent profile model fit indices (Masyn, 2013), several indices compared the model fit across models. The fit statistics, suggested by current best practices in mixture modeling, were: Bayesian information criterion (BIC), sample size adjusted BIC (saBIC), consistent Akaike information criterion (CAIC), approximate weight of evidence criterion (AWE), Bayes factor (BF), correct model probability (cmP), bootstrap likelihood ratio test (BLRT; McLachlan & Peel, 2000), and Vuong–Lo–Mendell–Rubin LRT (VLMR-LRT; Vuong, 1989). Lower information criterion values suggest a better model fit among the models compared (Nylund et al., 2007). Higher BF values and cmP values provide more robust evidence to the specific model as the best fitting relative to other models considered (Masyn, 2013). The BLRT and the VLMR-LRT tests compare the fit of a  $k$ -class model with a  $k - 1$  class solution. Significant  $p$  values ( $p < 0.05$ ) suggest there is evidence supporting the  $k$  class solution compared to the  $k - 1$  class model (Nylund et al., 2007). Classification diagnosis of profiles' separation was conducted with high average posterior class probability (AvePP; i.e.,  $> 0.70$ ) and odds of correction classification ratio for Class  $k$  ( $OCC_k$ ; i.e.,  $> 5$ ), evaluating classification precision and separation (Masyn, 2013; Nagin, 2005).

In step 2, after confirming the final model for this study, the manual BCH method (Nylund-Gibson et al., 2019) examined profiles' association with students' social emotional strengths and psychological distress. Several demographic variables (i.e., students' socioeconomic circumstances, ethnicity, gender identity, and sexual orientation) were included as control variables. The manual BCH method was favored because it minimizes class shifting with auxiliary variables and can simultaneously assess the demographic covariates and distal outcomes of profiles (Asparouhov & Muthén, 2013). Wald tests assessed the significance of distal outcomes' estimated means differences between profiles, and

the demographic covariates were regressed on the latent profiles and each outcome.

In step 3, we calculated the proportion of classification agreement between the two classification methods to assess classification congruence. Each student's profile membership was coded according to their most likely assigned latent profile and also classified into *Flourishing*, *Languishing*, and *Moderate* groups following the MHC-SF categorical diagnostic scheme. The two sets of groupings were compared by cross-tabulation to assess classification congruence between the two methods.

## Results

Tables 1 and 2 show descriptive information of the variables in the analysis. The overall Covitality score of psychological strengths showed large and positive correlations with all three dimensions of well-being (i.e., emotional, psychological, and social). Psychological distress had moderate and negative correlations with the three types of well-being.

### Model Selection

Table 3 displays the fit statistics of each Model estimated. The 1–8 class models converged for both Models 1 and 4. However, Model 2 did not converge after a 3-profile solution, and Model 3 did not converge after a 2-profile solution. Comparing across all converged models, we observed that Model 4 generally exhibited a better fit than Model 1 across the 1–8 profile solutions, as shown by the lower information criteria statistics, suggesting Model 4 provided a better fit to the data. In Model 4, the information criteria decreased for each additional class, but the decreasing magnitude became smaller after the fifth profile solution. However, the LMR-LRT indicated a six-profile solution in Model 4. Since the information given by fit statistics seemed to suggest a 4–6 profile solution, we examined these profiles closely.

The four-profile solution showed two ordered groups (consistently high and consistently low well-being across each of the three aspects of well-being)—the two profiles between the two ordered groups varied by responses to

**Table 2** Correlations between study variables

Variables	1	2	3	4	5
1. Emotional well-being	–				
2. Social well-being	.76	–			
3. Psychological well-being	.86	.83	–		
4. Psychological strengths	.65	.63	.70	–	
5. Psychological distress	–.46	–.36	–.39	–.29	–

All  $p < .001$

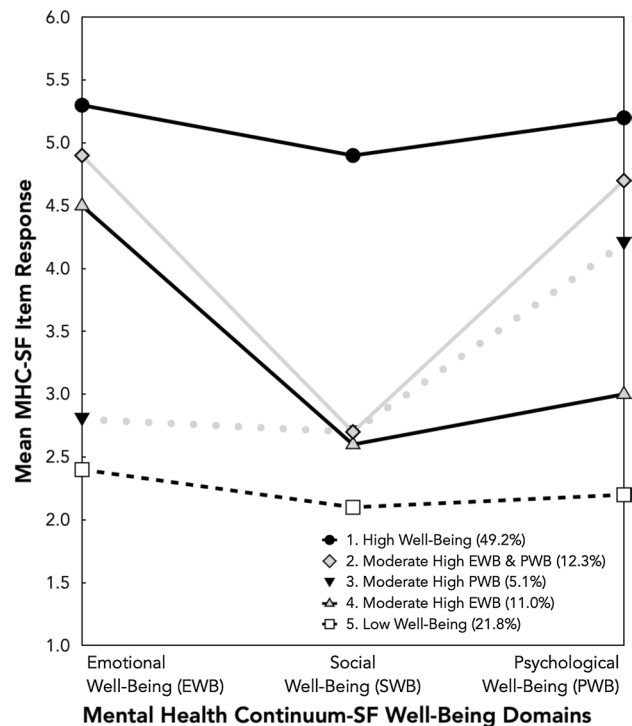
**Table 3** Fit statistics for LPA class enumeration (n=10,880)

	<i>k</i>	LL	BIC	saBIC	CAIC	AWE	BLRT <i>p</i>	VLMR-LRT <i>p</i>	<i>BF</i>	<i>cmP</i>
Model 1	1	-58,891.76	117,844.71	117,825.64	117,850.71	117,923.89	–	–	<.001	<.001
	2	-49,425.82	98,953.62	98,826.79	98,963.62	99,085.60	<.001	<.001	<.001	<.001
	3	-45,535.66	91,214.09	91,036.53	91,228.09	91,398.86	<.001	<.001	<.001	<.001
	4	-44,034.34	<b>88,252.24</b>	<b>88,023.95</b>	<b>88,270.24</b>	<b>88,489.80</b>	<.001	<.001	<.001	<.001
	5	-43,450.04	87,124.43	86,845.41	87,146.43	87,414.79	<.001	<.001	<.001	<.001
	6	-43,017.39	86,299.92	85,970.17	86,325.92	86,643.07	<.001	<.001	<.001	<.001
	7	-42,598.02	85,501.98	85,121.49	85,531.98	85,897.91	<.001	<.001	<.001	<.001
	8	-42,244.11	84,834.95	84,403.73	84,868.95	85,283.68	<.001	<.001	<b>1</b>	<b>1</b>
Model 2	1	-58,891.76	117,844.70	117,825.64	117,850.70	117,923.89	–	–	<.001	<.001
	2	-47,842.72	95,818.01	95,653.13	95,831.01	95,989.58	<.001	<.001	<.001	<.001
Model 4	1	-45,301.13	90,694.04	90,665.44	90,703.04	90,812.82	–	–	<.001	<.001
	2	-44,004.33	88,141.23	87,976.36	88,154.23	88,312.80	<.001	<.001	<.001	<.001
	3	-43,100.80	86,374.96	86,159.36	86,391.96	86,599.33	<.001	<.001	<.001	<.001
	4	-42,628.32	85,470.80	85,204.46	85,491.80	85,747.95	<.001	<.001	<.001	<.001
	5	-41,991.62	<b>84,238.19</b>	<b>83,921.12</b>	<b>84,263.19</b>	<b>84,568.13</b>	<.001	<.001	<.001	<.001
	6	-41,712.25	83,720.24	83,352.44	83,749.24	84,102.98	<.001	<b>&lt;.001</b>	<.001	<.001
	7	-41,518.19	83,372.91	82,954.38	83,405.91	83,808.44	<.001	.017	<.001	<.001
	8	-41,352.88	83,083.08	82,613.82	83,120.08	83,571.40	<.001	.022	<b>1</b>	<b>1</b>

*K* number of classes, *LL* model log likelihood, *BIC* Bayesian information criterion, *saBIC* sample size adjusted BIC, *CAIC* consistent Akaike information criterion, *AWE* approximate weight of evidence criterion, *BLRT* bootstrapped likelihood ratio test, *VLMR-LRT* Vuong–Lo–Mendell–Rubin adjusted likelihood ratio test, *pp* value, *BF* Bayes factor, *cmP* correct model probability; **Bold**=best fit statistic for each individual statistic. Model 1 indicates fixed variance across classes and no covariances specified. Model 2 indicates within-class variance are specified; Model 3 (within-profile covariance specified) was not listed because the models did not converge after 1 class. Model 4 indicates covariances specified for the overall model and fixed variance across classes

the three well-being indicators. All profiles showed similar patterns in the five-profile solution, like those in the four-profile solution, with an added group between the two ordered profiles. However, the additional profile showed qualitative differences compared to the other four profiles, which had a profile size of 5%. In contrast, the added group in a six-profile solution did not show a qualitative difference relative to other profiles. Thus, considering both statistical and conceptual merits (Muthén, 2003), a five-profile solution was selected.

Figure 2 shows the five-profile solution patterns and profile sizes. The profiles labels are (a) *High Well-Being*, (b) *Moderate High EWB & PWB*, (c) *Moderate High PWB*, (d) *Moderate High EWB*, and (e) *Low Well-Being* based on the patterns of the three profile indicators. Thus, there were two ordered profiles (i.e., High Well-Being and Low Well-Being) and three profiles spanning the two ordered profiles with different combinations of responses to the three aspects of well-being. As shown in Table 4, the five-profile solution demonstrated good separation and classification precision, indicating that individuals across profiles were highly differentiated, and individuals within profiles had considerably similar response patterns (Masyn, 2013; Nagin, 2005).



**Fig. 2** Five-profile solution for the Mental Health Continuum-Short Form (MHC-SF) domains



**Table 4** Model classification diagnostic for a five-profile solution

Five-profile solution	<i>k</i> -class proportions	95% CI	<i>mcaPk</i>	<i>AvePPk</i>	<i>OCCk</i>	Entropy
1. High well-being	0.49	[0.478, 0.506]	0.499	0.938	15.62	0.818
2. Moderate high EWB and PWB	0.12	[0.111, 0.141]	0.123	0.799	27.90	
3. Moderate high PWB	0.05	[0.044, 0.061]	0.051	0.789	67.16	
4. Moderate high EWB	0.11	[0.099, 0.127]	0.110	0.790	29.58	
5. Low well-being	0.22	[0.206, 0.229]	0.218	0.895	30.64	

*EWB* emotional well-being, *PWB* psychological well-being, *mcaPk* modal class assignment proportion for Class *k*, *AvePPk* average posterior class probability, *OCCk* odds of correction classification ratio for Class *k*

## Demographic Correlates of Mental Health Profiles

Table 5 shows the results of demographic correlates of the latent profiles. Profiles differed mainly by students' sexual orientation and ethnic identities. The High Well-Being profile was the reference group. There were significantly more students who identified as a sexual minority in the three lowest mental health profiles (i.e., Low Well-Being, Moderate High PWB, and Moderate High EWB). Students of Color were also more likely to be in the Low Well-Being and Moderate High PWB profiles. Our results indicated that more female students belonged to the Low Well-Being and Moderate High PWB profiles, controlling the 20.7% of

respondents whose gender identity was not included. The findings suggest that several demographic characteristics (i.e., gender identity, ethnic minority, and sexual orientation) were associated with high school students' membership in the five mental health profiles.

## Profiles' Association with Distal Outcomes

Table 6 shows the means of all outcomes in each latent profile. Each profile displayed different patterns in positive and negative adjustments with students' demographic characteristics considered. For example, students in the High Well-Being profile reported the healthiest adjustment, as

**Table 5** Students' demographic correlates of the five-class solution with the high well-being profile (profile 1) as the reference group

Mental health class	Variable	<i>Logit</i>	<i>SE</i>	<i>OR</i>
2. Moderate high EWB and PWB	Female	0.32**	0.11	1.37
	No response gender item	-0.25	0.23	0.78
	Sexual minorities	0.31	0.16	1.36
	Students of color	0.20*	0.09	1.22
	FRMP	0.14	0.10	1.15
3. Moderate high PWB	Female	0.15	0.14	1.16
	No response gender item	0.27	0.24	1.31
	Sexual minorities	1.13***	0.16	3.09
	Students of color	0.33**	0.12	1.39
	FRMP	0.44**	0.14	1.55
4. Moderate high EWB	Female	-0.11	0.10	0.89
	No response gender item	-0.06	0.16	0.94
	Sexual minorities	0.51***	0.14	1.67
	Students of color	0.21**	0.06	1.23
	FRMP	0.19	0.13	1.21
5. Low well-being	Female	0.24*	0.11	1.28
	No response gender item	0.03	0.10	1.03
	Sexual minorities	1.29***	0.11***	3.64
	Students of color	0.30***	0.06	1.35
	FRMP	0.31**	0.10	1.37

*EWB* emotional well-being, *PWB* psychological well-being, *OR* odds ratio, *FRMP* free and reduced meal program

\* $p < .05$ ; \*\* $p < .01$ ; \*\*\* $p < .001$

**Table 6** Mean and standard errors of distal outcomes across mental health profiles (response range 1–4)

Mental health profiles	Psycho-logical strengths	Psychological distress
1. High well-being	3.17 (.02) <sup>a</sup>	1.64 (.04) <sup>c</sup>
2. Moderate high EWB and PWB	2.95 (.02) <sup>b</sup>	1.83 (.06) <sup>b</sup>
3. Moderate high PWB	2.75 (.03) <sup>c</sup>	2.52 (.07) <sup>a</sup>
4. Moderate high EWB	2.59 (.02) <sup>d</sup>	1.89 (.03) <sup>b</sup>
5. Low well-being	2.33 (.01) <sup>e</sup>	2.45 (.03) <sup>a</sup>

PWB psychological well-being, EWB emotional well-being; means that do not share superscripts differ at  $p < .01$  on pairwise Wald tests of equality for distal outcomes across profiles

evidenced by the highest psychological strengths scores and lowest psychological distress. Conversely, students in the Low Well-Being profile exhibited the lowest psychological strengths and more psychological distress. The remaining three groups spanning the High and Low Well-Being profiles presented different psychological strengths and distress levels.

### High Well-Being Profile

The High Well-Being profile was the largest group (49.2%). Students reported the highest well-being (MHC-SF item responses *every day* and *almost every day*) across emotional, social, and psychological dimensions. Consistently, students in this profile experienced the lowest psychological problems (most item responses were *never* and *1–2 times*). In addition, students in this profile were more likely to exhibit higher psychological strengths than other profiles.

### Moderate High EWB and PWB Profile

Students in the Moderate High EWB & PWB (12.3%) reported frequent positive emotional and psychological well-being experiences (MHC-SF responses of *every day* and *almost every day*) and low levels of social well-being (MHC-SF responses slightly lower than *once a week*). These students' reported levels of psychological strengths were close to those in the High Well-Being profile. These students tended to have a medium but lower psychological distress than the students in the High Well-Being profile.

### Moderate High PWB Profile

The Moderate High PWB profile (5.1%), the smallest, included students experiencing low emotional and social well-being (MHC-SF responses less than about *once a week*) and moderately high level of psychological well-being (most

responses about *two or three times a week*). These students reported medium levels of psychological strengths and distress. They had higher psychological strengths than students in the Low Well-Being students but lower than High Well-Being students. In addition, they experienced more psychological distress than their counterparts in the High Well-Being profile.

### Moderate High EWB Profile

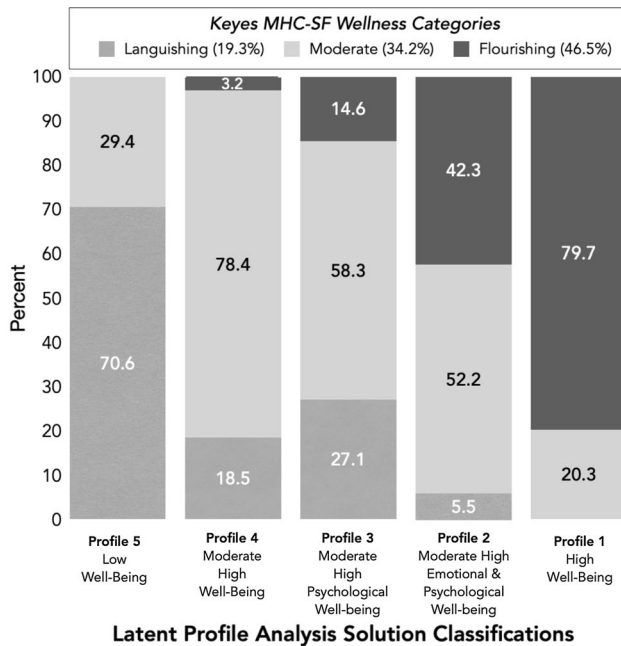
The Moderate High EWB (11.0%) reported medium–high emotional well-being (most item responses about *two or three times a week*) but low social and psychological well-being (most item responses less than to approximately *once a week*). These students reported medium levels of psychological strengths and distress. Students in this latent profile had higher psychological strengths than those in the Low Well-Being profile in all three aspects but lower than those in the High Well-Being profile. In addition, they experienced more psychological distress than their counterparts in the High Well-Being profile.

### Low Well-Being Profile

The Low Well-Being profile was 21.8% of the study sample and reported the lowest rating (item responses about *once or twice*) of all three MHC-SF indicators compared to all other profiles. In addition, these students showed the lowest psychological strengths and the highest psychological distress, as expected.

### LPA and MHC-SF Classification Congruence

We examined classification congruence between the LPA and the Keyes' MHC-SF categorical diagnostic method to interpret the emerging latent profiles. The overall and profile-specific classification using LPA and the Keyes categorical diagnostic method was highly congruent, as shown in Fig. 3. For the overall sample, there were slightly more students belonging to the groups with High Well-Being mental health (49.3%) in the latent profile analysis relative to Keyes' Flourishing group (46.5%). Similarly, slightly more students belonged to the Low Well-Being profile (21.8%) than the Keyes Languishing category (19.3%). Figure 3 shows students' percentage within each latent profile labeled Flourishing, Moderate Mental Health, and Languishing in terms of the classification congruence within each latent profile. Within the two proportionately largest latent profiles, both High and Low Well-Being profiles had over 70% of students identified congruently as Flourishing and Languishing, respectively. The remaining students in these two profiles were labeled in the Keyes Moderate Mental Health



**Fig. 3** Classification congruence between the latent profile analysis five-profile solution and Keyes' Mental Health Continuum Categories (Note Two Profile 5 youths (.01%) were in Keyes' Flourishing category)

category. These results indicate high classification consistency between the two classification methods regarding students with the highest and lowest mental health.

Concerning the three profiles spanning the High and Low Well-Being profiles, the Moderate High EWB & PWB profile had 52.2% of individuals placed in Keyes' Moderate Mental Health group and 42.3% classified Flourishing. This incongruent group (5.1% of the total sample) had low scores on social well-being but rated *every day* or almost *every day* on the six psychological well-being items. Regarding the remaining two latent profiles, approximately 80% of students within the Moderate High EWB profile and 60% of the Moderate High PWB profile were placed in the Moderate Mental Health group using Keyes' MHC-SF diagnostic approach. Regarding the incongruence between classification methods, 27.1% of the Moderate High PWB and 18.5% of the Moderate High EWB profile were classified as Languishing. However, these incongruent groups were small, representing 1.2% and 2.0% of the total sample.

## Discussion

This current study explored students' mental health profiles based on their emotional, social, and psychological well-being responses to understand US adolescents' mental health and the use of the MHC-SF in school-based screening and

monitoring efforts. Additionally, we compared methods categorizing youths' well-being using LPA and the MHC-SF categorical diagnostic approach (Keyes, 2005). Recognizing that it is easier to know how to support students with the highest and lowest well-being level, our analyses focused on understanding students' moderate well-being range.

## Five Mental Health Profiles

Using LPA, five mental health profiles (i.e., High Well-Being, Moderate High EWB & PWB, Moderate High PWB, Moderate High EWB, and Low Well-Being) emerged in the current study's sample. The profiles differentiated students based on their self-report of their psychological strengths and psychological distress with optimal functioning among students in the High Well-Being profile. The five-profile categorization revealed that students in the moderate range reported different well-being levels across emotional, social, and psychological well-being. These heterogeneities were related to different functioning levels across the distal outcomes of psychological strengths and distress, suggesting the need for a closer look into groups in the moderate response range. Targeted interventions for students in the three *Moderate* response range profiles may be more effective if they refer to their unique needs. Moreover, comparing the two classification approaches in this study revealed a more thorough understanding of response patterns among Keyes' Moderate Mental Healthy category.

Consistent with the current study's hypothesis, the High and Low Well-Being profiles reported similar functioning levels across the three dimensions of emotional, social, and psychological well-being. The current study extended previous dual continua research findings by identifying unique response patterns among students in the Keyes moderate mental health group. Profile membership was significantly associated with students' psychological strengths and distress. The High and Low Well-Being profiles showed unique psychological strengths and distress levels. Students in the High Well-Being profiles experienced the highest levels of psychological strengths and the lowest levels of psychological distress, with the inverse for the Low Well-Being profile. However, among the three moderate range latent profiles, there were diverse well-being levels in psychological, social, and emotional dimensions related to different psychological strengths and distress levels. For instance, the Moderate High PWB group showed adequate psychological strengths, but these students also reported an equivalent level of psychological distress compared with the Low Well-Being profile. Hence, the response patterns over the three dimensions of well-being among students with moderate mental well-being indicate possible different intervention needs. Differentiated functioning among students with moderate range mental health was reported in another recent study, showing

college students reported different levels of life satisfaction and purposeful lifestyle across six mental health categorizations (Xiao et al., 2021). The six categorizations were based on respondents' positive mental health (high, moderate, and low) and the presence of depression symptoms. Our results extended their findings by showing that individuals with moderate mental health differ in depressive symptoms and present distinctive well-being patterns across the three dimensions. These findings suggest potential benefits accruing from educators' strategically attending to students within the moderate mental health continuum zone.

### US Adolescents' Well-being and Classification Insights from LPA

The current study classified nearly half of the high school students as Flourishing (Keyes categorical diagnostic approach) or High Well-Being (LPA approach). The proportion of US students with positive mental health was larger than Keyes' study (2006), with 36% of students in the Flourishing group among adolescents (ages 12–18 years) but similar to the study using US college samples (49.3%; Keyes et al., 2016). A higher percentage of students identified as Languishing or Low Well-Being (19.3%, 21.8%, respectively) in this study relative to 6.0% Languishing (Keyes, 2006). Furthermore, similar to previous research among US students (Keyes, 2005; Keyes et al., 2012), this study found that students' reported social well-being level was lower than psychological and emotional well-being. Among the emerging latent profiles, the three moderate range and the Low Well-Being profiles, comprising half of the respondents, indicated that they experienced social well-being less than once a week. This finding reflects the substantial need to promote US high school students' social well-being.

Mental health classifications using the empirically driven approach and the categorical diagnostic method were considerably congruent. Apart from our empirical evidence reflecting the need to evaluate students' social well-being as a distinct and separate dimension from psychological well-being, several psychometric studies have shown that the three subscales of the MHC-SF are correlated but meaningfully different (Keyes, 2005; Lamers et al., 2011). The emerging latent profiles in the three moderate mental health profiles also considerably overlapped with Keyes' categorical diagnostic approach in our findings. However, the three moderate range profiles exhibited different response patterns, reflecting differentiated support needs, including Moderate Mental Health using the categorical diagnostic method.

### Implications and Future Research

The heterogeneities among students in the three moderate well-being profiles call for researchers and educators to

identify the differentiated needs of students in the moderate mental health continuum range, namely those not experiencing either high or low well-being levels. Although these students may not be at the highest risk, students in the moderate mental health range show a considerably higher risk than students classified in the *Flourishing* category (Keyes, 2007, 2016). Keyes (2014) states, "If you want better mental health, you must focus on positive mental health—promoting flourishing and protecting against its loss. Public health and organizations cannot promote mental health by solely reducing mental illness, and no amount of wishful thinking will make this fact disappear" (p. 189). Correspondingly, schools can forestall students declining from Flourishing to Moderate Mental Health or Moderate Mental Health to Languishing. These efforts recognize that preventing the loss of mental well-being is one cornerstone of school mental health services. Our findings inform educators of the differentiated needs of students in the moderate mental health range by identifying at least three groups of students in the three moderate well-being profiles. For example, the means of individual student's responses on the three mental health subscales can be compared to the profiles in Fig. 2 when considering services for students. Targeted interventions can be designed for them based on their unique well-being profiles. For instance, students in the Moderate High EWB profile may need interventions focusing on character strengths and school membership due to their low psychological and social well-being levels. However, future research is warranted to effectively distinguish differentiated needs among the moderate well-being students and design targeted interventions. Latent transition analysis may help address this research question by exploring the antecedents and characteristics of students transitioning across profiles and identifying the factors that predict movement from the Moderate High EWB to High Well-Being.

Results indicated that over half of the US adolescents self-reported feelings of social well-being less than once a week. School-based universal mental health programs to effectively foster students' sense of community and meaningful engagement are urgently needed. Research on promoting students' social well-being in a school context is limited, but strategies that promote school climate and school belonging provide evidence-supported possibilities (Allen et al., 2021). More research on understanding the determinants and predictors of social well-being is needed, particularly in light of current social events occurring after data collection, including political divisiveness and experiencing more social isolation due to a global COVID-19 pandemic.

Both the diagnostic and LPA approach classification methods appear useful for their intended purposes, with generally congruent groupings. The categorical diagnostic process can help quickly identify *Languishing* students, leading to efficient early referrals to prevent future detrimental

consequences. Meanwhile, the nuanced approach of examining emotional, social, and psychological well-being through LPA provides granular picture of how students differ in the three dimensions. A detailed examination of response profiles is particularly relevant when students have widely divergent responses to the MHC-SF items. For instance, two respondents in this study reported “almost every day” or “every day” on six items from PWB and SWB subscales and one EWB item, whereas these two students were assigned to Low Well-Being in LPA due to their low average on each subscale. Although these divergent response profiles appear to be rare, LPA may be a useful approach to identify the risks and needs of students with widely divergent response patterns.

The analysis offered through LPA could inform intervention planning and highlights the importance of focusing on different dimensions of well-being for students depending on their particular MHC-SF profile. We acknowledge that LPA is not an easily accessible classification method for practitioners. However, a more detailed examination of students’ scores across the various emotional, social, and psychological well-being levels may provide insights into tailoring interventions for different student groups. The LPA analyses coupled with the examination of distal outcomes conducted here offer compelling reasons to suggest that nuanced interventions may help students with varying levels of well-being across emotional, social, and psychological domains. Interventions targeting students’ different well-being dimensions promote students to achieve complete mental health by enhancing mental health and building students’ resilience in facing psychological distress. However, more research is needed to examine these interventions and practical ways to identify differences among the Moderate Mental Health students while preserving subscales information.

## Limitations

Despite its contributions, the current study has limitations. First, only California public high school students participated in this study. LPA is an empirically driven analysis, meaning that the emerging mental health profiles specific to this sample and replication studies would support these classifications. Different numbers and configurations of profiles could emerge when using other samples. Further exploration of LPA using different samples on this MHC-SF scale or other measures will be beneficial to further understanding adolescents’ well-being. Second, consistent with recommendations, the selected five-class latent profile solution was chosen based on statistical evidence and conceptual considerations. We do not contend that this is the best solution or that the five profiles comprehensively represent US high school students’ mental health—further research involving diverse samples is needed. However, this

study’s chosen five-class solution supports the hypothesis that students in the moderate well-being zone have different and unique profiles deserving targeted school services and research attention.

Third, we did not know 20.7% of the participants’ gender identity in this dataset. Several analyses were conducted to assess and control the impact of lacking gender identity information of this group of participants on the results. A sensitivity analysis revealed that profiles did not emerge differently between samples with and without information on the gender identity item. The results showed nonsignificant relationships with distal outcomes for students without gender identity information. This evidence ensured that including the students without gender identity information did not have a meaningful impact on the findings. Fourth, the binary gender identity question used in the survey requires improvement. There is emerging recognition that using a question asking students “what is your sex?” and offering the binary male–female options can be misleading and not inclusive. Even though this long-used item format uses the word “sex,” it is increasingly recognized that it was, at a minimum, referring to students’ understanding of their birth gender assignment, without offering broader gender identification options. Thus, given the significant associations between gender identity and sexual orientation found in the current study, future research contributions should examine MHC-SF profiles with larger samples of diverse gender and sexual orientation identifying adolescents.

## Conclusion

The Keyes categorical diagnostic method and the LPA empirical classification approach were highly congruent among those with the highest and lowest well-being levels. Moreover, the emerging profiles indicate that Keyes’ Moderate Mental Health students had varying emotional, social, and psychological well-being levels. Three moderate well-being range profiles emerged with distinct well-being patterns. The current study identified potential benefits for considering the full range of students’ mental health well-being profiles—high, low, and moderate—to tailor multitier school mental wellness fostering services.

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## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

**Ethics Approval** This study used publicly available data. The Human Subjects Committee at the authors' university has confirmed that no ethical approval is required.

**Consent to Participate** Passive consent was obtained from legal guardians of the participants. Student assent was requested and obtained prior to survey administration.

**Consent to Publish** No identifying information about participants is available in the article.

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