Instruments for Dual-Factor Mental Health Screening in Elementary Schools: Implications in Mental Health Classification

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Abstract

This research study holds practical significance for educators, school administrators, and mental health professionals. The study utilized structural equation modeling on two samples of elementary school students in grades three to five to create and validate condensed versions of the Social-Emotional Health Survey-Primary and the Me and My School questionnaire. These abbreviated scales exhibited strong internal validity and reliability across grade levels and genders, allowing for the assessment of wellness and distress among a diverse range of elementary school students. Furthermore, data from a longitudinal sample investigated dual-factor mental health profiles and their consistency over one year. Based on the newly validated scales, the wellness and distress indicators revealed three distinct profiles: *Flourishing*, *Moderate*, and *Languishing*. The transitions of students across these profiles emphasize the importance of routine mental health screening, at least once annually, to identify and address students' needs.

Keywords: dual-factor mental health model, mental health screeners, elementary school, schoolwide mental health screening

Instruments for Dual-Factor Mental Health Screening in Elementary Schools: Implications in Mental Health Classification

Universal school-based mental health screening is the first step in supporting children's and youth's mental health in a multi-tiered system of support (MTSS; Eklund & Dowdy, 2014). The dual-factor mental health (DFM) model offers an expanded view of school-based mental health based on a preventive approach to support vulnerable students and foster all students' well-being (Greenspoon & Saklofske, 2001; Keyes, 2007; Suldo & Shaffer, 2008). This framework conceptualizes mental health along two continua—subjective well-being and psychopathology (Suldo & Shaffer, 2008). Instead of solely relying on distress symptoms to distinguish students at mental health risks, the expanded DFM model can identify students who report having a low quality of life but do not report substantial distress symptoms (Keyes, 2005). Students exhibiting lower quality of life (e.g., global life satisfaction) have shown vulnerability to impaired functioning and deteriorating mental health, even though they do not exhibit high levels of distress (Keyes, 2002; Moore et al., 2019). To support this approach for screening, psychometrically sound and brief screeners for subjective well-being and psychological distress are essential. There have been relatively limited options for self-reporting mental health screeners for elementary school students (Bruhn et al., 2014; Splett et al., 2014).

The present study addresses the practical need for brief versions of the Social-Emotional Health Survey-Primary (SEHS-P; Furlong et al., 2013) and the Me and My School (Deighton et al., 2013; M&MS) questionnaires among elementary school students in in grades three to five. We used the brief scales to classify DFM profiles using a data-driven method, mixture modeling, to explore emergent profiles and the emergent profiles' stability over a year. The findings of this study will inform DFM screening in elementary schools by providing psychometrically sound instruments for assessing students' subjective well-being and distress and unveiling the stability of DFM profile transitions across mental health profiles over a year.

Dual-Factor Mental Health Model

Several scholars proposed DFM model conceptualizing mental health as two dimensions: subjective well-being and psychopathology (Greenspoon & Saklofske, 2001; Keyes, 2002; Suldo & Shaffer, 2008), intending to capture individuals at all points in the continuum of mental health needs. Keyes (2007) identified three primary mental health groups: flourishing (high subjective well-being and low distress), languishing (low subjective well-being and high distress), and moderate mental health (individuals who are not flourishing or languishing). Similar concepts but with distinctive classifications, Suldo and Shaffer (2008) proposed and observed four mental health groups: high subjective well-being with low psychopathology (i.e., complete mental health), low subjective well-being with high psychopathology (i.e., troubled), low subjective well-being with low psychopathology (i.e., vulnerable), and high subjective well-being with high psychopathology (i.e., symptomatic but content). It was argued that assessing students' subjective well-being is warranted because subjective well-being and complete mental health are necessary for optimal developmental and academic outcomes (Antaramian et al., 2010; Chan et al., 2022; Moore et al., 2019). Over time, students who are not flourishing are more likely to experience languishing mental health (Keyes, 2002). Hence, DFM aligns well with contemporary efforts to move school-based mental health services toward a preventive and promotive direction (Eklund & Dowdy, 2014). This preventative approach is particularly crucial in the face of the pressing mental health needs among children in the U.S. and elsewhere (Bitsko et al., 2022; Murthy, 2021), emphasizing the urgency and importance of this study.

Screening Tools for Elementary School Students

Current mental health screening tools for elementary school students are limited. According to Splett and colleagues’ (2014) review of school-based screening tools, the Student Risk Screening Scale (SRSS) and Strengths and Difficulties Questionnaire (SDQ) are two open-access scales that assess externalizing behaviors, school attitudes, and peer relations (Drummond, 1994; Goodman, 1997). The Devereux Student Strengths Assessment (DESSA) System is used to measure students’ social-emotional competence and resilience from kindergarten to eighth grade (LeBuffe et al., 2009). However, these existing scales primarily focus on externalizing behaviors and school-related issues, with limited attention to students’ subjective well-being. Most scales for elementary school students rely on teachers’ or parents’ reports rather than students’ own reports (Levitt et al., 2007). Nevertheless, self-report internalizing problem rating scales for elementary school students have shown satisfactory validity for third-graders and older students (Chan et al., 2021; Merrell et al., 2002). Highlighting the importance of student self-reports, Cunningham and Suldo (2014) found that teachers accurately identified only about 50% of students at risk of depression and anxiety, missing more than 15% of students experiencing similar levels of distress symptoms. Utilizing elementary school students’ self-reports contributes a crucial perspective to school-based mental health screenings.

In our study, we aimed to validate shorter versions of two mental health screeners for subjective well-being and internalizing distress among students in grades three to five. We utilized the SEHS-P (Chan et al., 2021; Furlong et al., 2013) and the M&MS questionnaire (Deighton et al., 2013). The SEHS–P assesses the covitality concept comprising four students' psychological strengths (i.e., gratitude, optimism, zest, and persistence) among elementary school students from third to fifth grade. The original SEHS-P consists of 20 items measuring gratitude, optimism, zest, and persistence. In positive psychology research, gratitude, optimism, zest, and persistence are highly related to youths' mental health and developmental and school outcomes, representing a triadic positive orientation towards life (e.g., Furlong et al., 2009; Park et al., 2004). These four psychological strengths also represent elementary students' well-being, capturing an appreciation of good things that happen and feeling thankful, being hopeful for positive outcomes, approaching life with anticipation, vigor, and energy, and endurance in accomplishing goals or tasks (Furlong et al., 2013; Peterson & Seligman, 2004). The SEHS-P has demonstrated good validity among elementary school students in the U.S. (Chan et al., 2021), China (Wang et al., 2016), and Japan (Iida et al., 2021), showing robust correlations with classroom satisfaction, school belonging, and prosocial behaviors.

The M&MS questionnaire measures emotional-behavioral challenges among students aged 8-12, initially developed for national mental health interventions in the U.K. (Patalay et al., 2014). Previous research provided evidence supporting the M&MS questionnaire's use to identify clinical clients from general samples (Patalay et al., 2014) with convergent validity with the Strengths and Difficulties Questionnaires (Deighton et al., 2013). The M&MS questionnaire measures emotional-behavioral challenges among students aged 8-12, initially developed for national mental health interventions in the U.K. (Patalay et al., 2014). The M&MS questionnaire adequately identified clinical clients from general samples (Patalay et al., 2014) and demonstrated strong convergent validity with the Strengths and Difficulties Questionnaires (Deighton et al., 2013). Its factorial structure, validity, and reliability were satisfactory among U.S. students in Grades 4-6 (Moffa et al., 2021). The current study further validates a brief version of the scale among third- to fifth-grade U.S. students. These two brief screeners potentially provide school practitioners with accessible, empirically supported instruments to facilitate DFM screening.

Empirical Approach to Dual-Factor Mental Health Classification

Mixture modeling is a data-driven classification method that seeks to identify unique profiles based on participants' response patterns to critical indicators (Nylund-Gibson et al. method's 2023). This empirical, exploratory method identifies profiles based on the pattern of responses to subjective well-being and distress items. For instance, previous studies with secondary students have identified two main profiles: complete mental health and troubled profiles (e.g., Clark & Malecki, 2022; Moore et al., 2019; Reinhardt et al., 2020). While the specific profiles may vary across studies, they have consistently found that different profiles are associated with significantly different functioning levels (Clark & Malecki, 2022; Moore et al., 2019). For example, individuals with high wellness and low distress (i.e., complete mental health or flourishing) demonstrated better overall social and emotional functioning (Clark & Malecki, 2022; Suldo et al., 2016).

Conversely, students with low subjective well-being and high distress profile (i.e., troubled or languishing) had lower grade point averages (GPA) and poorer self-efficacy (Suldo et al., 2011). To evaluate the application of the two screeners in categorizing DFM profiles, we validated the psychometric properties of the two screeners. Our study assessed how well they function as indicators to classify students' DFM profiles and employed mixture modeling to uncover DFM profiles. By avoiding cutoff scores due to the unavailability of norm scores, our research contributes to understanding students' DFM mental health classification and stability.

Mental Health Stability Among Elementary School Students

Assessing the stability of children's mental health profiles is crucial in designing effective universal screening programs, including determining the optimal timing and frequency of assessments. A review of existing literature involving middle and high school students, revealed that students who belong to the high subjective well-being and low distress profile (i.e., complete mental health or flourishing) are the most stable, with between 61% to 86% of students remaining in the same profile over a year or two years among elementary and secondary school students (Compton, 2016; Kelly et al., 2012; McMahan, 2012; Moore et al., 2019; Petersen et al., 2022). On the other hand, students who do not belong to the complete mental health or flourishing profile experience more instability (Compton, 2016; Kelly et al., 2012; Moore et al., 2019). The profile of moderate subjective well-being but high distress (i.e., symptomatic but content) has mixed evidence for stability, with some studies finding this profile to be the second most stable behind complete mental health (Compton, 2016; Kelly et al., 2012), while others find it to be the least stable (McMahan, 2012). Besides the symptomatic but content profile, Kelly and colleagues (2012) found that the low subjective well-being and low distress (i.e., vulnerable) profile was the least stable. In contrast, Moore and colleagues (2019) observed that the low subjective well-being and high distress (i.e., troubled) profile was the least stable.

The inconsistencies found in the few existing longitudinal DFM profiles underscore the potential contributions of our research. By revealing the types of emergent profiles and the stability of mental health profiles among elementary school students from third to fifth-grade levels, our study offers school professionals another approach with which to identify vulnerable students. This knowledge can guide the implementation of timely interventions, potentially averting the worsening of mental health issues among students.

Current Study

Considering the need for and use of brief measures to support mental health screening in schools and the relatively limited self-report measures at the elementary school level, this study first used two independent cross-sectional samples to develop and validate brief versions of the SEHS-P and the M&MS questionnaire. The SEHS-P intends to capture elementary school students' social-emotional strengths, representing their mental health wellness, and the M&MS questionnaire assesses children's experiences of emotional-behavioral challenges. After assessing the psychometric properties of the abbreviated scales, we evaluate the application of the two scales in classifying students' DFM profiles and the stability of the emergent mental health profiles over a year using mixture modeling on an independent longitudinal sample. The study has four research purposes: (a) developing the brief versions of SEHS-P and M&MS, (b) evaluating the internal validity and reliability of the brief scales, (c) assessing the measurement invariance of the brief scales across gender and grade levels, and (d) exploring DFM profiles indicated by the two brief scales and their stability over a year.

The study's objective is to develop reliable and efficient self-report measures for universal DFM mental health screening in elementary school settings. The two measures will be used to categorize DFM profiles and evaluate their effectiveness in identifying students with varying mental health needs. By examining the stability of emerging mental health profiles, the study will provide insights into the developmental paths of DFM profiles in childhood, helping to determine the timing and frequency of universal mental health screening required in elementary schools. DFM screening will enhance the provision of comprehensive, promotive, and preventive tiered support to students with diverse needs.

Method

Participants

The study used three independent subsamples from a larger dataset of students' responses from five elementary schools in California from 2021 to 2023. Cross-sectional Sample 1 was employed to develop brief versions of the SEHS-P and M&MS questionnaires based on their item loadings, factorial structure, measurement invariance across gender and grade levels, and item content. Cross-sectional Sample 2 was employed to assess the brief scales' internal validity. Longitudinal Sample 3 evaluated the application of the two scales in classifying DFM profiles.

Cross-Sectional Sample 1: Brief Versions of the SEHS-P and M&MS

Sample 1 had 489 elementary school students. We employed Sample 1 to develop brief versions of the SEHS-P and the M&MS questionnaires. Participants in this sample responded to a survey in 2021 when they were in third grade (27.4%), fourth grade (38%), and fifth grade (34%). Most spoke English at home (72%), 8.6% spoke Spanish, 16% spoke both Spanish and English, and 3.5% spoke other languages at home. All respondents responded to the survey in English. The racial/ethnic identification of the participants included: 47.9% White, 20.9% Latinx, 3.3% Black, 4.6% Asian, 7.3% Native American /Pacific Islander, and 14.6% Others. The sample included 50.1% boys, 44% girls, 3.3% prefer not to answer, and 2.7% non-binary.

Cross-Sectional Sample 2: Internal Validity and Measurement Invariance

Sample 2 consisted of 328 students who only responded to the survey in 2023. We removed one student who went to alternative family education due to the unique circumstances of their educational setting. Sample 2 evaluated the psychometric properties of the brief versions of the SEHS-P and the M&MS questionnaires. Participants were in third grade (65.7%), fourth grade (20.1%), and fifth grade (14.3%) in 2023. Most spoke English at home (64.1%), 12.5% spoke Spanish, 19.1% spoke both Spanish and English, and 4.3% spoke other languages at home. All respondents responded to the survey in English. The racial/ethnic identification of the participants included: 42.9% White, 30.4% Latinx, 3.4% Black, 3.4% Asian, 5.5% Native American /Pacific Islander, and 14.4% Others. The sample included 52.3% boys, 41.3% girls, 4.3% prefer not to answer, and 2.1% non-binary.

Longitudinal Sample 3: Application in Dual-Factor Mental Health Classification

Sample 3 included a subgroup of participants who completed two waves of the annual mental health survey from 2022 to 2023. Sample 3 consisted of 225 participants aged between 8 and 11 years. We used this sample to explore students' DFM profiles and their stability across a year. Students were in third grade (71.6%), fourth grade (28%), and fifth grade (0.4%) in 2022. 72.9% of respondents chose English as the primary language they spoke at home, 9.3% selected Spanish, 15.1% selected Spanish and English at home, and 2.7% selected other languages. All respondents responded to the survey in English. The racial/ethnic identification of the participants included: 44.2% White, 21.9% Latinx, 4% Black, 5.4% Asian, 8% Native American /Pacific Islander, and 16.5% Others. The sample included 48.4% boys, 45.3% girls, 5.8% prefer not to answer, and 0.4% non-binary.

Procedures

Classroom teachers proctored the administration following a standardized script that was part of an annual student wellness survey. Students completed the survey during school hours after giving their consent. Parents provided passive consent following the standard procedures (see http://chks.wested.org/administer/instructions). The Human Subjects Committee at the authors' university approved the study protocol.

Measures

Wellness Indicators: Social-Emotional Health Survey-Primary

The 20 SEHS-P items assess *gratitude* (five items, e.g., Do you feel thankful to go to your school?), *optimism* (five items, e.g., Do you expect that you will feel happy during class time?), *zest* (five items, e.g., Do you get really excited about your schoolwork?), and *persistence* (five items, e.g., Do you finish all of your class assignments?), which summed to provide an overall covitality factor (Furlong et al., 2013). The psychometric properties of the original SEHS-P were satisfactory for U.S. elementary school students and best represented by a second-order model (Chan et al., 2021). We developed an 8-item SEHS-P based on Samples 1 and 2, consisting of two items representing each subscale. A four-point response scale was used (1 = *no, never,* 2 = *yes, some of the time*, 3 = *yes, most of the time*, 4 = *yes, all of the time*). Afterward, we used the factor scores derived from the second-order model of SEHS-P to capture covitality as profile indicators in mixture modeling. Among Sample 3, the scale's omega coefficients were .77 in 2022 and .83 in 2023.

Distress Indicator: Me and My School Questionnaire (M&MS)

The M&MS questionnaire (Deighton et al., 2013) is a tool that examines emotional and behavioral difficulties, primarily focusing on emotional distress with a four-point response format (1 = *never*, 2 = *sometimes*, 3 = *often*, 4 = *always*). The original 10-item M&MS questionnaire was validated among U.S. elementary school students and represented by a one-factor model (Moffa et al., 2021). The original 10-items cover sleep issues (e.g., I wake up in the night), social distress (e.g., I feel shy), and emotional distress (e.g., I worry when I am at school). Samples 1 and 2 supported a brief M&MS version with six items, a reliable alternative based on confirmatory factor analysis results. We used the factor scores of the six items represented by a one-factor model at each wave as profile indicators. Among Sample 3, the omega coefficients of the brief M&MS were .72 in 2022 and .74 in 2023, further confirming its reliability.

Demographic Covariates

Students' ethnic and gender identities were included as covariates in the latent transition analysis (LTA), considering their effects on children's mental health (e.g., Brown et al., 2007;

Yoon et al., 2023). Students responded to a gender identity item with four responses (*girl, boy, prefer not to answer, non-binary*) with boys as the reference group. Due to the small number of respondents picking *prefer not to answer,* we grouped them as missing values. Students reported seven ethnic identities (*American Indian*, *Asian*, *Black or African American*, *Native Hawaiian or Pacific Islander*, *Latinx*, *White*, or *Mixed Race*), categorized into White, Latinx, and Others for the analysis with White as the reference group.

Preliminary Analysis of Missing Data

The three independent samples were not statistically different in gender and race/ethnicity based on the chi-square tests; however, the distribution of the students in the three independent samples varied by grade level. Regarding missing values of the wellness and distress items in each independent subsample, there were 0.2% to 0.6% of missing data. The percentages of the missing values were in an acceptable range (Dong & Peng, 2013). All models were estimated under the missing-at-random (MAR) assumption (Enders, 2010) using full information maximum likelihood (FIML) to handle missing data.

Data Analysis

We conducted the confirmatory factor analyses (CFA) on Rstudio with the lavaan package (Rosseel, 2016) and latent transition analysis (LTA) on Mplus 8.10 (Muthén & Muthén, 2017) using maximum likelihood estimation with robust standard errors (MLR), considering the negative skew of some of the profile indicators. The analyses primarily involved (a) assessing psychometric properties of the brief SEHS-P and M&MS and (b) exploring DFM profiles and their stability using latent transition analysis.

Samples 1 and 2: Assessing Psychometric Properties

To develop brief versions of the SEHS-P and M&MS questionnaire, we first conducted

CFA to assess items' loadings on Sample 1. Item selection was determined by considering item loadings, content, and theory. For the SEHS-P, we aimed to maintain a comprehensive representation of the covitality construct's four dimensions (Furlong et al., 2013). For the M&MS questionnaire, we also aimed to keep items representing a wide range of emotional and behavioral distress experiences (Deighton et al., 2013). In addition to individual item performance, we rigorously evaluated model fit by employing CFI, RMSEA, and SRMR. Acceptable model fit statistics were CFI > .90, RMSEA < .08, and SRMR < .08 (Hu & Bentler, 1999). Because we aimed to develop brief scales that show invariance across grade levels and gender groups, we thoroughly examined the measurement model across grade levels (Grades 3, 4, and 5) and gender groups (boys and girls). We assessed three levels of invariance, including configural invariance (same number of factors and pattern of fixed and freely estimated parameters held across groups), metric invariance (fixing factor loadings to be same across groups), and scalar invariance (fixing factor loadings and item intercepts to be equal). We evaluated invariance by comparing the change of model fit as suggested by Chen (2007; ΔCFI < .01 and ΔRMSEA < .015 or ΔSRMR < .03) and chi-squared difference tests. After confirming the brief versions of each scale based on Sample 1's results, we further assessed the factorial structure and reliability of the brief scales using Sample 2.

Sample 3: Latent Transition Analysis (LTA)

The latent transition analysis consisted of four steps: (a) conducting class enumeration at the two waves respectively, (b) performing measurement invariance to test the measurement models of each wave, (c) exploring structural LTA model specifications, and (d) assessing the associations of students' gender identity and race/ethnicity with the optimal LTA model following Nylund-Gibson and colleagues' recommendations (2023).

In step 1, we used the factor scores of covitality from the brief SEHS-P and the factor scores of the M&MS scale as profile indicators to estimate 1- to 7-class models at each wave. The final model reflected a thorough evaluation based on the relative fit indices of the plausible competing models, conceptual merits, and profiles' meaning (Masyn, 2013). We employed a range of robust statistical tests including Akaike information criterion (AIC), 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) to compare models. Lower information criterion values suggest a better model fit among the models compared (Nylund-Gibson et al., 2019). 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 the *k-class* solution is better than the $k-1$ class model (Nylund et al., 2007).

In step 2, we specified a nested model (i.e., an invariant model) and a parent model (i.e., a freely estimated model) for comparison. Establishing measurement invariance involves assessing configuration similarity across model waves. Invariance of the latent profiles across waves merits model parsimony, ease of interpretation, and more flexibility for specifying structural parts of latent transition models (Nylund-Gibson et al., 2023). The log-likelihood ratio test-Satorra and Bentler (LRT-SB) was used to compare the invariant and freely estimated model measurement models, with nonsignificant results indicating invariance (Satorra & Bentler, 2010). The decision of whether constraining the estimators in the measurement models across waves to be equivalent in the LTA model was based on statistical results, the patterns of emerging profiles, and theoretical rationales (Nylund, 2007).

In steps 3 and 4, we specified the structural parts of the LTA model. Then, we used the

Bolck, Croon, and Hagenaars (BCH) approach to assess the relations of demographic variables with emergent profiles in each wave (Asparouhov & Muthén, 2014; Nylund-Gibson et al., 2023).

Results

Samples 1 and 2: Factorial Structure and Measurement Invariance of SEHS-P

Prior empirical studies and theoretical rationales support the SEHS-P second-order model comprising a higher-order factor (covitality) and four subfactors (Chan et al., 2021; Furlong et al., 2013; Wang et al., 2016). Therefore, a second-order model was the hypothesized model for the SEHS-P. First, a series of CFAs assessed the item loadings of the second-order model using Sample 1. Based on the model fit indices, items' factor loadings, and items' meaning, we removed three items for each subscale, resulting in eight items with two under each subscale. Table 2 shows the factor loadings of the 8-item scale.

For invariance testing, we examined the measurement model of the 8-item SEHS-P across grade levels (Grades 3, 4, and 5) and gender groups. Scalar invariance was achieved, suggesting that the meaning of the construct (e.g., self-esteem) and items (e.g., I feel good about myself) were interpreted equivalently across groups (see Table 3). Afterward, we further validated a second-order model structure of the 8-item SEHS-P using Sample 2, which yielded a satisfactory model fit, item loadings, and internal reliability (see Table 1).

Samples 1 and 2: Factorial Structure and Measurement Invariance of M&MS

Our analyses involved a series of factor analyses and invariance testing on Samples 1 and 2 to develop a brief M&MS questionnaire. We followed a similar approach to the one we used with the SEHS-P, starting by evaluating the factorial structure and item loadings of the 10 M&MS items using Sample 1. This process involved examining the loadings of each item, with a particular focus on the two items related to sleep quality. The results showed that these two items had loadings lower than 0.4. Based on this, we decided to remove these two sleep items from the questionnaire.

Further analyses did not find metric invariance for the 8-item scale across grade levels. We then examined the factor loadings of the items across grade levels and removed two items that revealed larger differences in factor loadings across grade levels (i.e., *I feel like nobody likes me* and *I feel scared*). The overall factor structure of a one-factor model resulted in adequate model fit and item loadings. (see Tables 1 and 4). The analysis supported full measurement invariance for the 6-item M&MS scale across gender and grade levels (see Table 5). We also validated the revised M&M scale using Sample 2, showing adequate model fit, item loadings, and internal reliability (see Tables 1 and 4).

Sample 3: Dual-Factor Mental Health Profiles and Stability

To apply the brief screeners for classifying mental health profiles, we estimated 1 to 7-profile solutions with different model structures indicated by the factor scores of the covitality and distress indicators independently for 2022 and 2023. However, the models after the 4-profile solutions had convergence problems. Table 6 shows the fit statistics of class enumeration in each year. In 2022, the VLMR-LRT, BLRT, and all information criteria statistics indicated a three-profile solution. In 2023, the VLMR-LRT identified a four-profile solution, and the BLRT was significant for all profiles. The information criteria statistics indicated different solutions. AIC and saBIC continued to drop from 1- to 4-profile solutions, but BIC and CAIC suggested a 3-profile solution. The profile configurations of the solutions in 2022 were similar to those in 2023. Considering the mixed evidence based on the relative model fit statistics and lacking qualitative differences in the additional profile in the 4-profile solution in 2023, we selected the three-profile solution for 2023. The entropies for the solutions in 2022 and 2023 were 0.87 and 0.70, respectively. We then conducted invariance testing to assess whether the profiles were similar in their measurement models across years. The LRT-SB result was $\chi 2diff(15) = 5.49$, $p = .31$, meaning that statistical testing supported measurement invariance.

Thus, we specified the structural parts of the LTA model with full measurement invariance. Figure 1 shows the patterns and sizes of each year's profiles in the final LTA model. Following Keyes' (2007) conceptualization of mental health conditions, the three profiles were labeled *Flourishing*, *Moderate*, and *Languishing*. The *Flourishing* profile was indicated by a higher-than-average wellness level and a lower-than-average distress level, with profiles of 81% in 2022 and 69% in 2023. The *Moderate* profile was characterized by approximately average wellness and distress levels, with profiles of 17% in 2022 and 26% in 2023. The smallest profile in both years was the *Languishing* profile, with a lower-than-average wellness level and a higher-than-average distress level (2022: 2%; 2023: 5%). The size of the *Moderate* profile increased by approximately 9% from 2022 to 2023, but the size of the *Flourishing* profile decreased by roughly 12%.

Table 7 offers a comprehensive view of the transition probabilities in our final LTA model, highlighting student well-being's dynamic and complex nature. For instance, the *Flourishing* and *Moderate* profiles demonstrated high stability, with 84% of students remaining in the Languishing profile and 97% staying in the *Moderate* profile in 2023. However, it is essential to recognize the variability in student well-being, as around 57% of students in the *Languishing* profile transitioned to the *Moderate* profile. For *Flourishing* students in 2022, 12% moved to the *Moderate* profile, and 4% moved to the *Languishing* profile. For students in the *Moderate* profile, 3% regressed to the *Languishing* Profile.

Table 8 shows the regression coefficients and odd ratios for the effects of students' demographic characteristics (e.g., gender and race/ethnicity) on profiles' membership each year. The results showed no significant variations in students' gender and racial/ethnic distributions across profiles in both years.

Discussion

This study used two independent samples to develop and preliminarily validate brief versions of the SEHS-P and M&MS to address the limited accessibility of mental health screeners for elementary school students' subjective well-being and internalizing distress. Furthermore, to evaluate the two brief screeners in classifying DFM profiles, we employed a third longitudinal sample to explore mental health profiles indicated by the covitality indicator from the brief SEHS-P and a distress indicator from the brief M&MS as well as their stability across a year. The factor analyses and measurement invariance supported an eight-item SEHS-P and a six-item M&MS. This suggests their validity and reliability in examining subjective well-being and distress symptoms among third to fifth-graders. We also observed three emergent latent profiles aligned with the mental health profiles proposed by Keyes (2007). The results corroborated the application of the two screeners in identifying elementary school students' DFM profiles. Moreover, our findings added to the limited literature on the stability of DFM profiles among elementary school students. The transient nature of elementary school students with *Languishing* mental health, as observed in our findings, highlights the importance of regular monitoring of their mental health and schoolwide mental health promotion for students.

Brief SEHS-P and M&MS

Our findings with Samples 1 and 2 supported the factorial structure of an eight-item SEHS-P represented by a second-order model with two items measuring each of the four dimensions and a six-item M&MS represented by a one-factor model. Both revised screeners' measurement models were invariant across third- to fifth-grade students and boys and girls. The invariance testing supported the assumptions that students from third to fifth grades and identified as boys or girls interpreted the items, similarly, allowing direct comparisons of the scores across these groups. These preliminary findings supported the application of the two brief screeners to assess subjective well-being and distress symptoms using self-report data from elementary school students from third to fifth grades. Although there is a need for more replication studies using different samples for broader applications in schools, this study was an initial step to validate these two brief screeners, which are easy to use and open access. It validated measures for supporting effective screening of elementary school students through the DFM model to tackle one of the common barriers to mental health screening (Bruhn et al., 2014).

Dual-Factor Mental Health Profiles

Moreover, the emergent mental health profiles indicated by the two screeners also provided alternative validity to the application of the scales in DFM screening, as shown by the three emergent profiles (i.e., *Flourishing, Moderate, Languishing*) in alignment with the theoretical assumptions and prior empirical studies (Clark & Malecki, 2022; Kelly et al., 2012; Keyes et al., 2002; Moore et al., 2019). Although some studies with adolescents found more profiles, such as four profiles in Kelly et al. (2012) and Moore et al. (2019) and five profiles in Petersen et al. (2012), such differences across studies were likely contributed by different indicators including, students' grade levels, and methodological approaches. For instance, the profile indicators in Petersen et al. (2012) comprised subjective well-being, emotional difficulties, and behavioral concerns. Similar to other studies of elementary school students, the most well-functioning profile was the largest (Compton et al., 2016; Petersen et al., 2022), whereas our results had high proportions of students in the *Flourishing* profile. Moreover, the DFM profiles demonstrated similar patterns across a year with the support of measurement invariance. Although prior studies did not always find statistical support for measurement invariance of DFM profiles across years, likely due to the large number of parameters involved in the model rather than meaningful differences, the configuration of profiles tended to be similar across years from studies using different age groups (Moore et al., 2019; Petersen et al., 2022).

Transition and Stability of Students' Membership in Mental Health Profiles

Many students from the *Flourishing* and *Moderate* profiles stayed in the same profiles from 2022 to 2023. Our results echo prior studies and theories, suggesting *Flourishing* students (i.e., high wellness and low distress) demonstrated highly stable and positive mental health developmentally (Compton, 2016; McMahan, 2012; Moore et al., 2019), and approximately 12% of them moved to the *Moderate* profile, and 4% moved to the *Languishing* profile from 2022 to 2023. The proportion of students in the *Flourishing* profile transitioning profiles was similar to Petersen et al. (2022) using a two-year longitudinal dataset collected from elementary school students in the U.K. Moreover, students in the *Moderate* profile also had very high stability, with only 3% regressing to the *Languishing* profile in 2023. In contrast, over half of the students in the *Languishing* profiles transitioned to the *Moderate* profile, showing improved mental health. The likelihood of *Flourishing* students transitioning to *Languishing* or vice versa was very low. This pattern of movements implies that the proportion of students staying in high distress and low subjective well-being for over a year is minimal. Still, they are also unlikely to have optimal mental health conditions. Schoolwide promotive interventions to foster students' subjective well-being appear essential in supporting students in developing stable and optimal mental health conditions.

Practice Implications

The two brief DFM screeners have several practical implications for a schoolwide mental health screening practice. We provided a fillable screening form with the two screeners and scoring guidelines as *online supplementary materials*, which school counselors and psychologists can easily administer. The two brief DFM screeners reduce the cognitive load of longer self-report screeners, reducing the survey burden on students. It normalizes the screening process and conveys to students that this is part of a broader, healthy self-reflection process in a caring, supportive climate. Implementing schoolwide screening practice is part of an ongoing watch-care-response process, and offering students valid choices to participate in self-reflection surveys can positively affect their sense of personal agency. Agency is also supported when the school scrutinizes students' responses and provides positive support services to individuals and groups. The two DFM mental health screeners offered here are easily administered more than once a year with individual students, classes, or the entire school. DFM self-report survey serves the additional purpose of familiarizing students with responding to a social-emotional health survey early on in their school careers. Students begin to see what types of questions and response options surveys contain. They start to become familiar with the experience of reading an item or question and experience feelings and thoughts as they consider how that item or question describes who they are. Having the opportunity to do this in the safe confines of an elementary school classroom led by a caring teacher can normalize self-reflection surveys before adolescence and when students experience more complex social-emotional developmental challenges and tasks. When using DFM screening to address campus needs and enhance climate, students see that their survey responses helped to inform these improvements, reinforcing that the purpose of universal screeners is not just to "catch" students' problems but a wellness check for all students and the school itself as an entity.

Limitations and Future Research

Some limitations of this study should be noted. First, although the samples included in this study represented racial/ethnically diverse and gender-balanced elementary school students, replicating the study using other samples of elementary school students is essential to generalize the findings, such as whether the two brief scales show adequate psychometric properties and whether similar DFM profiles emerge and demonstrate similar stability in this developmental stage in more representative samples. Second, this study's approach, which combined some racial/ethnic groups and treated students who identified as "non-binary" and "prefer not to answer" as missing values due to their small sample sizes, may have overlooked within-group differences across different racially minoritized populations and the impact of other gender groups on mental health profiles. To address these limitations, we propose two critical future research directions: first, recruiting more samples from minoritized groups, and second, exploring DFM profiles by race/ethnicity and gender identity. These steps will help assess the applicability of this framework and mental health profiles across cultural groups and underscore the need for more inclusive research methods and the consideration of intersectionality in mental health studies.

Conclusion

This study validated the brief SEHS-P and M&MS mental health screeners for use in elementary schools. The two brief screeners displayed adequate internal validity and reliability across boys and girls in third to fifth grade. We also used the screeners to categorize students' mental health profiles and assess the profiles' stability over one year. The emergent *Flourishing, Moderate, and Languishing profiles* aligned with previous research, which supports using DFM measures in schoolwide screening with elementary school students. The results of this study have important implications for schools. First, the use of brief mental health screening tools like the SEHS-P and M&MS questionnaires can help schools identify students at risk of developing mental health problems based on the DFM model. Second, the study found that mental health among *Languishing* students was transient and fluid, and they are likely to move across mental health profiles. Therefore, schools should track students' mental health conditions and provide appropriate support when needed; these brief measures facilitate monitoring multiple times per school year. Our findings suggest that the two brief screeners are efficient tools for monitoring students' mental health conditions and informing interventions.

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Table 1

Fit Statistics of the Brief SEHS-P-8 and M&MS

Sample	*N*	χ^2	*df*	CFI	SRMR	RMSEA 90% [CI]	Omega
SEHS-P-8 Items							
Sample 1	484	57.496***	19	.944	.065	.065 [.047, .080]	0.83
Sample 2	326	22.84	19	.988	.061	.025 [.000, .054]	0.85
M&MS-6 Items							
Sample 1	486	25.704***	9	.966	.034	.062 [.037, .088]	0.83
Sample 2	326	31.766***	9	.940	.046	.078 [.059, .088]	0.88

Note. CFI = Comparative Fit Index; SRMR = Standardized. Root Mean-Square Residual; RMSEA = Root Mean-Square Error of Approximation.
***p < .001.

Table 2

Confirmatory Factor Analysis of the SEHS−P-8 items: Factor Loadings (Sample 1, n = 484)

Factors and Items	Loading	*SE*	*z*
Second-order Factor: Covitality			
Gratitude	.85	.04	2.41
Optimism	.90	.03	2.08
Zest	.92	.03	1.93
Persistence	.78	.04	3.38
First-order Factor 1: Gratitude			
1. Do you feel thankful to go to your school?	.75	.04	6.21
2. Are you thankful to have nice teachers at your school?	.52	.02	9.05
First-order Factor 2: Optimism			
3. Do you feel positive that good things will happen to you at school?	.62	.04	12.11
4. Do you expect that you will feel happy during class time?	.73	.04	7.55
First-order Factor 3: Zest			
5. Do you get really excited when you learn something new at school?	.59	.04	12.07
6. Do you wake up in the morning excited to go to school?	.60	.05	10.63
First-order Factor 4: Persistence			
7. When you get a low grade or test score, do you try even harder the next time?	.71	.06	6.46
8. Do you keep doing your class assignments even when they are really hard for you?	.56	.04	9.94

Table 3

SEHS-P-8 items: Invariance Testing of Grade Levels and Gender Groups (Sample 1, n = 484)

Invariance Comparison	χ^2	*df*	SRMR	RMSEA 90% [CI]	CFI	Model Comparison	Δ *S-B*χ^2	Δ *df*	ΔCFI	ΔRMSEA	ΔSRMR
Across Grade (Grades 3, 4, and 5)											
Model 1: configural invariance	99.235***	57	.067	.068 [.045, .089]	.940					–	–
Model 2: metric invariance	108.245***	65	.076	.064 [.043, .084]	.939	2 vs. 1	9.57	8	-.001	-.004	.009
Model 3: scalar invariance	112.907***	71	.078	.060 [.039, .080]	.940	3 vs. 2	5.62	6	.001	-.004	.002
Across Gender (Boys and Girls)											
Model 1: configural invariance	66.098***	40	.040	.053 [.032, .074]	.960						
Model 2: metric invariance	66.778***	47	.043	.043 [.018, .063]	.969	2 vs. 1	1.52	7	.009	-.010	.003
Model 3: scalar invariance	75.110***	54	.047	.041 [.017, .060]	.967	3 vs. 2	8.04	7	-.002	-.002	.004

Note. CFI = Comparative Fit Index; SRMR = Standardized Root Mean-Square Residual; RMSEA = Root Mean-Square Error of Approximation. ΔCFI < .01 and ΔRMSEA < .015 or ΔSRMR < .03 indicates non-invariance.
***$p < .001$.

Table 4

Confirmatory Factor Analysis of the M&MS-6 items: Factor Loadings (Sample 1, n = 484)

Items	Loading	*SE*	*z*
1. I feel lonely.	.72	—	—
2. I am unhappy.	.57	.07	9.39
3. How often do you worry?	.65	.08	9.85
4. How often do you cry?	.54	.09	9.66
5. I worry when I am at school.	.61	.09	8.96
6. I am shy.	.53	.08	10.78

Table 5

M&MS-6 items: Invariance Testing of Grade Levels and Gender Groups (Sample 1, n = 484)

Invariance Comparison	χ^2	*df*	SRMR	RMSEA 90% [CI]	CFI	Model Comparison	Δ $S\text{-}B\chi^2$	Δ *df*	ΔCFI	ΔRMSEA	ΔSRMR
Across Grade											
Model 1: configural invariance	50.604***	27	.040	.073 [.044, .102]	.954	—	—	—	—	—	—
Model 2: metric invariance	61.210***	37	.056	.064 [.036, .089]	.953	2 vs. 1	1.71	10	-.001	-.009	.016
Model 3: scalar invariance	155.902***	88	.060	.055 [.027, .080]	.955	3 vs. 2	4.38	10	.002	-.009	.004
Across Gender											
Model 1: configural invariance	27.986***	18	.040	.040 [.002, .081]	.975	–	–	–	–	–	–
Model 2: metric invariance	29.472***	23	.037	.035 [.000, .066]	.984	2 vs. 1	10.35	5	.009	-.014	.005
Model 3: scalar invariance	34.098***	28	.041	.031 [.000, .061]	.985	3 vs. 2	8.03	5	.001	-.004	.004

Note. CFI = Comparative Fit Index; SRMR = Standardized Root Mean-Square Residual; RMSEA = Root Mean-Square Error of Approximation. ΔCFI < .01 and ΔRMSEA < .015 or ΔSRMR < .03 indicates non-invariance.

***p < .001.

Table 6

Cross-Sectional Latent Profiles Enumeration Fit Statistics

2022	LL	*npar*	AIC	CAIC	BIC	saBIC	AWE	LRTS	VLMR-LRT	BLRT
1-class	-218.439	4	444.878	462.542	458.542	445.866	492.207	—	—	—
2-class	-197.380	7	408.760	439.673	432.673	410.488	491.585	42.118	0.002	< 0.001
3-class	**-175.369**	**10**	**370.738**	**414.899**	**404.899**	**373.207**	**489.060**	**44.022**	**0.004**	**< 0.001**
4-class	-187.161	13	400.322	457.731	444.731	403.532	554.141	-23.584	0.147	0.235
5-class	-184.291	16	400.582	471.240	455.240	404.532	589.897	5.740	0.302	0.333
6-class	-179.652	19	397.304	481.210	462.210	401.995	622.116	9.278	0.662	0.091
7-class	-176.723	22	397.446	494.600	472.600	402.878	657.754	5.858	0.374	0.667
2023	LL	*npar*	AIC	CAIC	BIC	saBIC	AWE	LRTS	VLMR-LRT	BLRT
1-class	-279.033	4	566.066	583.730	579.730	567.054	613.395	—	—	—
2-class	-248.952	7	511.904	542.817	535.817	513.632	594.729	60.162	0.444	< 0.001
3-class	**-236.116**	**10**	**492.232**	**536.393**	**526.393**	**494.701**	**610.554**	**25.672**	**0.492**	**< 0.001**
4-class	-228.940	13	483.880	541.289	528.289	487.090	637.699	14.352	0.047	< 0.001

Note. *K* – number of classes; LL = model log likelihood; AIC = Akaike information criterion; 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; p = p value; **Bold** = the selected model; Model 1 indicates fixed variances across profiles and no covariances specified. Model 1a indicates covariances specified for the overall model; Model 2 indicates within-profile variances are specified; Model 3 indicates within-profile covariances specified. Model 4 indicates within-profile variances and covariances. Fit statistics were not listed for models that did not converge.

Table 7

Latent Transition Probability Estimates of the Final LTA Model

	2023 Profile		
2022 Profile	Flourishing (68%)	Moderate (26%)	Languishing (5%)
Flourishing (81%)	**84%**	12%	4%
Moderate (17%)	0%	**97%**	3%
Languishing (2%)	0%	57%	**53%**

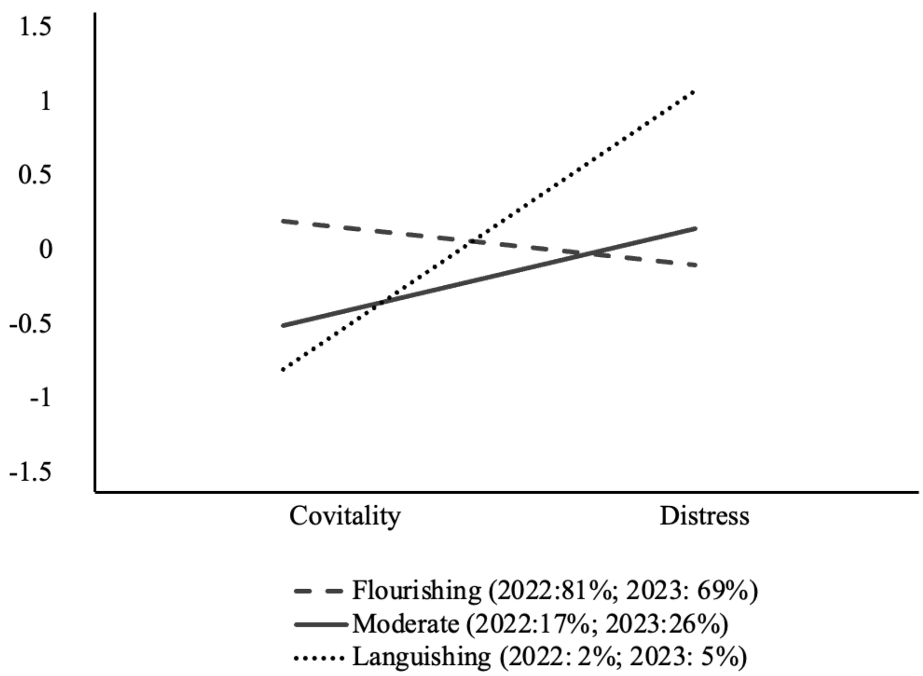
Table 8

Students' Demographic Correlates of the Three-Profile Solution with the Languishing Profile as the Reference Group

Mental Health Class	Variable	*Logit*	*SE*	*OR* (95% CI)
2022 Flourishing	Girl	-0.20	1.12	0.82 (0.09, 7.37)
	Latinx	-0.73	1.57	0.48 (0.02, 10.47)
	Other racial/ethnic groups	-1.31	1.32	0.27 (0.02, 3.56)
2022 Moderate	Girl	-0.81	1.23	0.45 (0.04, 5.00)
	Latinx	-0.39	1.69	0.68 (0.03, 18.76)
	Other racial/ethnic groups	-1.00	1.43	0.37 (0.02, 6.13)
2023 Flourishing	Girl	-1.29	0.92	0.27 (0.05, 1.68)
	Latinx	-2.16	1.48	0.12 (0.01, 2.08)
	Other racial/ethnic groups	-2.05	1.44	0.13 (0.01, 2.18)
2023 Moderate	Girl	-1.47	1.00	0.23 (0.03, 1.62)
	Latinx	-1.74	1.56	0.18 (0.01, 3.77)
	Other racial/ethnic groups	-1.88	1.52	0.15 (0.01, 3.02)

Figure 1

The Final Latent Transition Model with Profile Sizes



Contemporary School Psychology
Instruments for Dual-Factor Mental Health Screening in Elementary Schools:
Implications in Mental Health Classification, Online Supplemental Material

Student Survey
At my school...I feel

About me...	
At school I am in…	Grade 3 O Grade 4 O Grade 5 O

Practice	No, never	Yes, some of the time	Yes, most of the time	Yes, all of the time
Which circle says, "No, never?"	O	O	O	O
Which circle says, "Yes, some of the time?"	O	O	O	O
Which circle says, "Yes, most of the time?"	O	O	O	O

Instructions

These questions ask about how feel at school. This is not a test. There are no right or wrong answers. Choose the answer that is closest to how you feel.

How do you feel when you are at school?		No, never	Yes, some of the time	Yes, most of the time	Yes, all of the time
1	Do you feel thankful to go to your school?	O	O	O	O
2	Are you thankful to have nice teachers at your school?	O	O	O	O
3	Do you feel positive that good things will happen to you at school?	O	O	O	O

	How do you feel when you are at school?	No, never	Yes, some of the time	Yes, most of the time	Yes, all of the time
4	Do you expect that you will feel happy during class time?	○	○	○	○
5	Do you wake up in the morning excited to go to school?	○	○	○	○
6	Do you get excited when you are doing your classwork?	○	○	○	○
7	When you get a low grade or test score, do you try even harder the next time?	○	○	○	○
8	Do you keep doing your class assignments even when they are really hard for you?	○	○	○	○

	How often do you feel?	Never	Sometimes	Often	Always
9	I feel lonely	○	○	○	○
10	I am unhappy	○	○	○	○
11	How often do you worry?	○	○	○	○
12	How often do you cry?	○	○	○	○
13	I worry when I am at school	○	○	○	○
14	I am shy	○	○	○	○

Scoring

Social Emotional Health Survey-Primary (SEHS-P) Brief Total Raw Score

0 = No, never

1 = Yes, some of the time

2 = Yes, most of the time

3 = Yes, all of the time

Social Emotional Health Survey Primary (Brief Total Raw Score (range 0-24)

1	2	3	4	5	6	7	8	Sum

Me and my School (M&Ms) Brief Total Raw Score

0 = Never

1 = Sometimes

2 = Often

3 = Always

Me and My School (Brief) Total Raw Score (range 0-18)

1	2	3	4	5	6	Sum

Frequency of SEHS-P (Brief) x M&Ms (Brief) Response Patterns in Study Sample N - 1776

Me and My School (Brief)

Social Emotional Health Survey Primary (Brief)

					25th		50th		75th												
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	N
	24	10	9	7	11	9	2	4	1	3	2	1						1			60
	23	2	6	16	11	10	3	4	3	1			1		1						58
	22	8	6	15	10	10	15	7	6	5	2	2	1								87
	21	5	7	9	14	11	14	21	7	6	5	4	2	1		1					107
75th	20	7	13	12	18	18	19	30	11	6	3	1	2				1				141
	19	3	10	21	20	30	27	39	24	10	4	1	1	1	2	1					194
	18	5	8	9	16	20	28	31	22	8	5	6	1	1	2	2					164
50th	17	5	12	14	22	22	39	34	24	8	9	7	3	1	5						205
	16	3	4	6	15	21	18	21	22	12	9	4	2	2							139
	15	2	4	13	12	18	23	21	12	9	6	2	2	2	1						127
25th	14	1	3	4	7	11	17	20	13	10	9	3	3	2		2					105
	13	2	1	11	9	9	14	12	13	14	5	6	1	4	2	2	2				107
	12	1	5	3	5	10	7	14	7	11	5	10	4	4			1				87
	11	1		2	4	3	5	9	5	1	4	1	1	3		1		1			41
	10		2		4	3	4	9	4	1	4	3	5	1	2	3	1	1			47
	9			2		4	2	5	3	1	1	3	1	3	1	3					29
	8	2	2	4	1	3	1	2	2	6	2	2			1	4					32
	7			2	3		4	1	2	2	1	2	1	2	2						22
	6				2		1		2	1	1			2	1			1			11
	5	1			1	1	1			1		3				1					9
	4															1					1
	3								1						1						2
	2											1									1
	1																				0
	0																				0
	N	58	92	150	185	213	244	284	184	116	77	62	31	29	21	21	5	4	0	0	1776

SEHS-P (Brief) x M&Ms (Brief) Response Array Tracking Sheet

Me and My School (Brief)

Social Emotional Health Survey Primary (Brief)

					25th		50th		75th												
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	N
	24																				
	23																				
	22																				
	21																				
75th	20																				
	19																				
	18																				
50th	17																				
	16																				
	15																				
25th	14																				
	13																				
	12																				
	11																				
	10																				
	9																				
	8																				
	7																				
	6																				
	5																				
	4																				
	3																				
	2																				
	1																				
	0																				
	N																				

Original Source

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