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### Publication Date

2018

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UNIVERSITY OF CALIFORNIA

Santa Barbara

Exploration of Two Alternative Approaches to Dual-Continua Mental Health Classification  
among High School Students

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of  
Philosophy in Counseling, Clinical, and School Psychology

by

Kathryn Theresa Moffa

Committee in charge:

Professor Erin Dowdy, Chair  
Professor Michael Furlong  
Professor Karen Nylund-Gibson

September 2019

The dissertation of Kathryn Theresa Moffa is approved.

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Michael Furlong

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Karen Nylund-Gibson

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Erin Dowdy, Committee Chair

June 2018

Exploration of Two Alternative Approaches to Dual-Continua Mental Health Classification  
among High School Students

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by

Kathryn Theresa Moffa

## ACKNOWLEDGEMENTS

I am forever grateful for the many support systems that have enabled the completion of this dissertation, and every milestone leading up to this work. Words are not enough to show my gratitude for the endless love and support of my parents, who never doubted that this accomplishment would come. Thank you to Matt, my biggest cheerleader and consistent reminder that life is better with hugs, nature, and tacos. To Nick, Kelly, and the kids, thank you for welcoming me to any and every afternoon play session. And to Matt and Amy, who have taught me to think globally and act now.

This dissertation is also dedicated to my advisor, Dr. Dowdy, our research family, and my committee members, who tirelessly work in pursuit of bettering the lives of youths and families. I am forever appreciative of your intentionality and kindness during this process. To my cohort mates, thank you for managing to both challenge me and keep me laughing for the past four years.

VITA OF KATHRYN THERESA MOFFA  
May 2018

**Education**

---

- June 2019 (expected)  
(Combined)
- University of California, Santa Barbara**  
Ph.D. in Counseling, Clinical, and School Psychology  
Advisor: Erin Dowdy, Ph.D.
- June 2016
- University of California, Santa Barbara**  
Master of Education (M.Ed.)
- December 2012
- University of California, Los Angeles**  
B.A. in Economics, 2013  
College Honors

**Research Experience**

---

- Mar 2017 – Present
- Dissertation Research**  
Title: *Exploration of Two Alternative Approaches to Dual-Continua Mental Health Classification among High School Students*  
Chair: Erin Dowdy, Ph.D.  
Committee Members: Michael Furlong, Ph.D., Karen Nylund-Gibson, Ph.D.
- Collect cross-sectional schoolwide screening data for adolescents, grades 9 through 12, from approximately 45 high schools in California. Data includes information on mental health, at-risk behavior, and academic performance.
  - Conduct advanced statistical analyses, including latent profile analysis and receiving operating characteristic (ROC) curve analysis.
  - Results will be presented in two dissertation manuscripts submitted for publication.
    - Proposal accepted 06/2017
    - Data collection 10/2017 – 03/2018
    - Anticipated defense 06/2018
- Sept 2014 – Present
- Graduate Student Researcher**  
*International Center for School-Based Youth Development*

Advisors: Erin Dowdy, Ph.D., Michael Furlong, Ph.D., Karen Nylund-Gibson, Ph.D.

- Facilitate onsite data collection for schoolwide screening of approximately 2,000 students annually. Screening includes measures of social-emotional well-being and distress, at-risk and prosocial behaviors, and academic performance.
- Assist in consulting with school support teams to implement universal and targeted prevention and intervention strategies.
- Perform advanced-level data analytic strategies to establish and validate measures of social-emotional health.

Jan 2015 – Present

**Graduate Student Researcher**

***California Health Facilities Financing Authority (SB 82)***

***Grant***

*Santa Barbara County*

Advisor: Erin Dowdy, Ph.D.

- Develop measures to evaluate implementation and effectiveness of the Santa Barbara County crisis response system. Evaluation includes effectiveness of 24-hour crisis stabilization units, 30-day crisis residential treatment programs, mobile triage units, and crisis triage teams.
- Evaluate the level of satisfaction of sheriff and police departments with crisis response teams quarterly.
- Train staff members of the Santa Barbara crisis system in data collection procedures in compliance with approval from the university human subjects.
- Manage university human subjects research approval.

June 2017 – Sept 2017

**Graduate Student Researcher**

***IES Grant #R305A160157: Validation of a Measure to Assess the Social-Emotional Health of Secondary Students***

Advisors: Erin Dowdy, Ph.D., Michael Furlong, Ph.D., Karen Nylund-Gibson, Ph.D.

- Helped to facilitate onsite data collection for schoolwide screening of approximately 2,000 students.
- Conducted in-depth literature reviews on the development and use of measures proposed for universal screening as part of IES Grant #R305A160157
- Consulted with principal investigator (PI) and co-PI's to design and create electronic surveys to be taken across high schools in California.

Mar 2013 – June 2013

**Undergraduate Research Assistant**

***Center for Mental Health in Schools at UCLA***

*Department of Psychology, University of California, Los*

*Angeles*

Advisors: Howard Adelman, Ph.D. & Linda Taylor, Ph.D.

- Created resources for school administration and faculty focused on bullying prevention in schools.

Mar 2012 – Dec 2012

**Undergraduate Research Assistant**

***Social Interaction and Social Stigma Lab at UCLA***

*Department of Psychology, University of California, Los*

*Angeles*

Advisors: Jenessa Shapiro, Ph.D., & Shantal Marshall, Ph.D.

- Served as lead experimenter for a randomized controlled trial examining implicit bias and attitudes of prejudice among undergraduate students. Presented original presentations to research lab focused on relevant literature on implicit bias based on race, gender, sexual orientation, and ability. Collected preliminary data based on on-campus surveys with undergraduate students.
- Performed initial data entry and quality checked data entry.

**Publications**

---

Bertone, A., **Moffa, K.**, Wagle, R., Fleury, I., & Dowdy, E. (accepted with revisions). Considerations for mental health screening with Latinx dual language learners. *Contemporary School Psychology*.

Dowdy, E., Furlong, M.J., Nylund-Gibson, K., Moore, S., & **Moffa, K.** (2018). Initial validation of the social emotional distress survey-secondary to support complete mental health screening. *Assessment for Effective Intervention*.

**Moffa, K.**, Dowdy, E., & Furlong, M.J. (in press). Does including school belonging measures enhance complete mental health in schools? In K. Allen & C. Boyle (Eds.), *Pathways to belonging*. Rotterdam, Netherlands: Sense Publishers.

Furlong, M.J., Dowdy, E., Kim, E., **Moffa, K.**, Bertone, A., Yang, C., Ito, A. (2018). Assessment of Complete Social Emotional Health: An International School Psychology Perspective. In C. Hatzichristou & B.K. Nastasi (Eds.), *Handbook of school psychology in a global context*. Dordrecht, Netherlands: Springer.



Twyford, J., Buckley, L., **Moffa, K.**, & Dowdy, E. (2018). The strengths and difficulties questionnaire (SDQ): Factor Structure of the self-report form in Latino American youth. *Journal of School and Educational Psychology*.

**Moffa, K.**, Dowdy, E., & Furlong, M.J. (2016). Exploring the contributions of school belonging to complete mental health screening. *The Educational and Developmental Psychologist*. doi:10.1017/edp.2016.8

Dowdy, E., Raines, T., Dever, B., & **Moffa, K.** (2016). A preliminary investigation into the added value of multiple gates and informants in universal screening for behavioral and emotional risk. *Journal of Applied School Psychology*. doi:10.1080/15377903.2016.1165327

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

**Moffa, K.**, Adelman, H.S., & Taylor, L. (2013). A University Student's Perspective on Bullying Prevention in Public Schools. Retrieved from <http://smhp.psych.ucla.edu/pdfdocs/bullyingpeers.pdf>

### Technical Reports

Howard, A., Dowdy, E., & **Moffa, K.** (2016, 2017). Outcome and Process Evaluation Report: California Health Facilities Financing Authority (CHFFA) Grant (SB 82). Report submitted to Mental Health Services Oversight and Accountability Commission, State of California.

Howard, A., Dowdy, E., & **Moffa, K.** (2016, 2017). Outcome and Process Evaluation Report: Crisis Residential Programs (SB 82 Grant). Report submitted to Mental Health Services Oversight and Accountability Commission, State of California.

Howard, A., Dowdy, E., & **Moffa, K.** (2016, 2017). Outcome Evaluation Report: Triage Personnel Grant. Report submitted to Mental Health Services Oversight and Accountability Commission, State of California.

### Presentations

---

**Moffa, K.**, Moore, S., Dowdy, E., Furlong, M.J., & Nylund-Gibson, K. (February 2018). Initial validation of the Social-Emotional Distress Survey to support complete mental health screening. Poster presented at the National Association of School Psychologists Annual Convention. Chicago, IL.

- Wagle, R., Bertone, A., **Moffa, K.**, & Edyburn, K. (February 2018). Mental health screening in a culturally responsive way. Practitioner conversation presented at the National Association of School Psychologists Annual Convention. Chicago, IL.
- Swami, S., Golstein, A., Edyburn, K., & **Moffa, K.** (February 2018). An exploration of important issues in supervision. Practitioner conversation presented at the National Association of School Psychologists Annual Convention. Chicago, IL.
- Moffa, K.**, Dowdy, E., & Furlong, M. (February 2017). Exploring the contributions of school belonging to complete mental health screening. Presented at the National Association of School Psychologists Annual Convention. San Antonio, TX.
- Moffa, K.**, Dowdy, E., Dever, B.V., & Raines, T.C. (February 2017). A preliminary investigation into the added value of multiple gates and informants in universal screening for behavioral and emotional risk. Presented at the National Association of School Psychologists Annual Convention. San Antonio, TX.
- Twyford, J., **Moffa, K.**, Buckley, L., & Dowdy, E. (February 2017). Screening Latinx students with the strengths and difficulties questionnaire. Presented at the National Association of School Psychologists Annual Convention. San Antonio, TX.
- Bertone, A., Dowdy, E., Furlong, M. J., Moore, S. A., **Moffa, K.**, Carnazzo, K., & Garcia, M. G. (February 2017). Implementing universal complete mental health screening in high schools. Presented at the National Association of School Psychologists Annual Convention. San Antonio, TX.
- Dowdy, E., Furlong, M. J., **Moffa, K.**, Bertone, A., & Schell, J. (October 2016). The role of schoolwide complete mental health screening to foster student wellbeing. Presented at the California Association of School Psychologists Annual Conference. Newport Beach, CA.
- Dowdy, E., Furlong, M., Moore, S., **Moffa, K.**, & Bertone, A. (September 2016). The Use of Complete Mental Health Screening to Promote Student Social Emotional Health. Advanced Skills Session presented at the 21<sup>st</sup> Annual Conference on Advancing School Mental Health. San Diego, CA.
- Kim, E. K., **Moffa, K.**, Moore, S.A., & Widales-Benitez, O. (February 2016). Multiple profiles of mental health and quality of life among Korean adolescents. Advanced Skills Presentation presented at the National Association of School Psychologists Annual Convention. New Orleans, LA.
- Moore, S.A., **Moffa, K.**, Widales-Benitez, O., Dowdy, E., Furlong, M.J., & Carnazzo, K. W. (February 2016). Screening to identify internalizing distress using the DASS-21.

Presented at the National Association of School Psychologists Annual Convention.  
New Orleans, LA.

### **Clinical/Practicum Experience**

---

Aug 2017 – Present

#### **Graduate Student Clinician**

##### **Hosford Clinic/Parent-Child Interaction Therapy Clinic**

*University of California, Santa Barbara*

Supervisor: Miya Barnett, Ph.D.

- Implement parent-child interaction therapy (PCIT) with parents, caregivers, and their children, ages 2 to 7, with presenting problems related to oppositional defiant disorder, conduct disorder, attention-deficit/hyperactivity disorder, and trauma exposure.
- Monitor progress of parent and child in compliance with the Dyadic Parent-Child Interaction Coding System (DPICS), 4<sup>th</sup> Edition

Aug 2016 – June 2017

#### **Mental Health Externship Student**

##### **Santa Barbara Special Education Local Plan Area**

**(SELPA)**

*Lompoc Unified School District*

Supervisors: Travis Jenkins, Ed.S., PPS; Erin Dowdy, Ph.D

- Delivered evidence-based individual psychotherapy to individuals, ages 9 to 16, experiencing severe emotional and behavioral difficulties. Presenting problems were related to bipolar disorder, schizophrenia, depression, anxiety, autism spectrum disorder (ASD), attention deficit-hyperactivity disorder (ADHD), and post-traumatic stress.
- Utilized behavioral, cognitive-behavioral, motivational interviewing, and solution-focused approaches in psychotherapy.
- Planned and implemented social skills and social emotional learning curriculums for individuals, ages 9 to 12, with presenting problems related to ASD, ADHD, bipolar disorder, anxiety, and depression.
- Consulted with marriage and family therapists, school psychologists, general and special education teachers, and parents to implement intervention strategies for individual and classroom level support.

Aug 2016 – June 2017

- Participated in weekly supervision, during which case conceptualizations were presented and videotaped sessions were reviewed.

**Advanced Practicum Student**

**Santa Barbara Junior High, Santa Barbara, CA**

*Santa Barbara Unified School District*

Supervisors: Kym Ozbirn, M.Ed, NCSP; Erin Dowdy, Ph.D.

- Performed comprehensive evaluations of individuals, ages 12 to 14, including intellectual, cognitive processing, social emotional, behavioral functioning, and adaptive functioning assessments; observations; and parent, teacher, mental health clinician, and student interviews. Presented findings from evaluations to student support teams (SST) and collaborated to create and implement individual education and treatment plans.
- Delivered evidence-based individual counseling to individuals, age 13, with presenting problems related to specific learning disabilities, depression, anxiety, and attention.
- Utilized behavioral, cognitive behavioral, motivational interviewing, and brief solution-focused approaches in psychotherapy.
- Performed risk assessments for individuals experiencing suicidal ideation and plans for self-harm. Collaborated with Santa Barbara crisis intervention specialists, school administration, psychologists, and parents to create safety plans based on individuals' presenting concerns.
- Implemented and monitored individualized education plans (IEP), and targeted and intensive interventions.
- Consulted with school administration, teachers, and mental health clinicians to change and implement behavior intervention plans and targeted/intensive interventions.

Apr 2017 – May 2017

**Advanced Practicum Student**

**Learning Tree Preschool, Goleta, CA**

*Goleta Unified School District*

Supervisor: Misty Brewer, M.Ed., NCSP, Erin Dowdy, Ph.D.

- Performed comprehensive evaluations of individuals, ages 3-5, including cognitive processing, social emotional, behavioral functioning, and adaptive functioning assessments; observations; and parent and teacher

interviews. Presented findings from evaluations to student support teams (SST) and collaborated to create and implement individual education and treatment plans.

Mar 2016 – Oct 2016

**Graduate Student Clinician**

**Koegel Autism Center**

*University of California, Santa Barbara*

Supervisor: Ty Vernon, Ph.D.

- Implemented an empirically supported intervention, Pivotal Response Treatment (PRT), for children, ages 2 to 4, and their care givers, with presenting problems related to ASD.
- Monitored client progress based on language acquisition, communication skills, and social motivation and competence.

Aug 2015 – June 2016

**Practicum Student**

**Monroe Elementary School, Santa Barbara, CA**

*Santa Barbara Unified School District*

Supervisors: Melissa Quigley, M.Ed; Jill Sharkey, Ph.D.

- Performed comprehensive evaluations, including intellectual, cognitive processing, social emotional, behavioral functioning, and adaptive functioning assessments; observations; and parent, teacher, and student interviews. Presented findings from evaluations to student support teams (SST) and collaborated to create and implement individual education and treatment plans.
- Delivered evidence-based individual counseling to children, age 12, with presenting problems related to specific learning disabilities, conduct, depression, and attention.
- Delivered evidence-based group social skills and social emotional learning curriculum to children, ages 6 to 12, with presenting problems related to learning disabilities, ASD, attention, and conduct.
- Performed risk assessments for individuals experiencing suicidal ideation and plans for self-harm. Collaborated with Santa Barbara crisis intervention specialists, school administration, psychologists, and parents to create safety plans based on individuals' presenting concerns.

Jan 2015 – Mar 2015

**Psychology Practicum Student**

**Hosford Clinic, Santa Barbara, CA**

*Department of Counseling, Clinical, and School Psychology*  
Supervisor: Heidi Zetzer, Ph.D.

- Delivered individual psychotherapy to individuals, ages 19-22, and evaluated client progress based on subjective rating scales (Outcome Rating Scale, Working Alliance Inventory).
- Participated in weekly supervision meetings, during which videotaped sessions were reviewed.

Oct 2014 – June 2015

**Graduate Student Mentor**

**San Marcos High School, Santa Barbara, CA**

*Santa Barbara Unified School District*

Supervisor: Jill Sharkey, Ph.D

- Provided weekly mentorship to students, grades 9 through 12, as part of the Check, Connect, and Respect (CCR) program. Goals of mentorship included improving executive functioning skills, academic outcomes, social emotional health, and interpersonal relationships.

**Teaching Experience**

---

Fall 2017

**Teaching Assistant**

*Department of Counseling, Clinical, and School Psychology*  
University of California, Santa Barbara

- Cognitive Assessment

Winter 2017

**Teaching Assistant**

*Department of Counseling, Clinical, and School Psychology*  
University of California, Santa Barbara

- Psychology of Gender

Summer 2016

**Teaching Assistant**

*Department of Counseling, Clinical, and School Psychology*  
University of California, Santa Barbara

- College Student Peer Helping and Leadership

**Relevant Work and Volunteer Experience**

---

Oct 2014 – Dec 2014

**Student Assistant**

**Hosford Counseling and Psychological Services Clinic**

*Hosford Counseling and Psychological Services Clinic, Santa*

Barbara, CA

Supervisor: Dyan Wirt

- Led clients through check-in procedures prior to psychotherapeutic and psychiatric appointments, utilized a clinic-wide online data-management system to collect payments and store sensitive client information, and aided prospective clients with questions regarding clinic services.
  - Filed confidential patient information in compliance with HIPPA
- Oct 2013 – Sept 2014      **Paraeducator, Mild to Moderate Disabilities**  
*Brea-Olinda Unified School District, Brea, CA*
- Assisted two special education classes, grades 7 and 8, with mild to moderate learning disabilities. Responsibilities included carrying out behavior intervention plans, leading small groups of students in modified curriculum, and serving as an individual aide to a student with ASD in general and special education classes.
- Jan 2014 – June 2014      **Teaching Assistant, After School Program**  
*Fullerton Unified School District, Fullerton, CA*
- Coordinated and implemented an after-school program for children, ages 5-11, which included academic tutoring and educational projects and games. Served as liaison between site director and parents/caregivers concerning specific needs of families.
- Jan 2013 – June 2013      **Teaching Assistant, 2<sup>nd</sup> Grade**  
*Los Angeles Unified School District, Los Angeles, CA*
- Prioritized multiple clerical tasks while remaining a constant resource for teachers and students for behavior intervention plans and academic assistance. Communicated with administrators, teachers, and parents to best serve the needs of students.
- Summer 2012, 2013      **Activities Coordinator and Recruitment Team Member**  
*UCLA's Bruin Woods Family Camp, Lake Arrowhead, CA*
- Created and implemented engaging programs for typically developing youth and youth with mild disabilities, ages 6-18. Communicated with Camp Director and parents/caregivers to ensure satisfaction.
  - Conducted group and individual interviews with more than 200 applicants.
- Jan 2012 – Mar 2012      **Volunteer, 3<sup>rd</sup> and 4<sup>th</sup> grades**  
*Today's Fresh Start Charter School, Inglewood, CA*

- Provided academic assistance in small groups for students in the 3<sup>rd</sup> and 4<sup>th</sup> grades once per week.

### **Professional Service**

---

Sept 2017 – Present	Associated Students Committee Co-President Department of Counseling, Clinical, and School Psychology <i>University of California, Santa Barbara</i>
Jan 2015 – Present	Co-Reviewer, <i>School Psychology Quarterly</i>
Sept 2015 – Present	Co-Reviewer, <i>Journal of Psychoeducational Assessment</i>
Sept 2015 – Present	Co-Reviewer, <i>Assessment for Effective Intervention</i>
Oct 2016 – Aug 2017	Associated Students Committee Representative Department of Counseling, Clinical, and School Psychology <i>University of California, Santa Barbara</i>
Sept 2015 – June 2016	Climate Committee Member Department of Counseling, Clinical, and School Psychology <i>University of California, Santa Barbara</i>

### **Honors and Awards**

---

May 2018	Dissertation Grant Award <i>Society for the Study of School Psychology</i>
February 2018	Dean’s Travel Grant <i>University of California, Santa Barbara</i>
February 2017	Counseling, Clinical, and School Psychology Travel Grant <i>University of California, Santa Barbara</i>
February 2016	Counseling, Clinical, and School Psychology Travel Grant <i>University of California, Santa Barbara</i>
December 2012	Graduate of Honors College <i>University of California, Los Angeles</i>
Dec 2009 – Dec 2012	Alpha Lambda Delta and Phi Eta Sigma National Honors

Societies

*University of California, Los Angeles*

### **Professional Affiliations**

---

American Psychological Association  
National Association of School Psychologists  
California Association of School Psychologists



## ABSTRACT

### Exploration of Two Alternative Approaches to Dual-Continua Mental Health Classification among High School Students

by

Kathryn Theresa Moffa

Literature on school-based mental health has demonstrated that there is tremendous value in conceptualizing youths' mental health within the dual-continua model (DCM), which emphasizes that individuals' mental health is influenced by both their subjective wellbeing (SWB) and psychological distress. However, there are currently few guidelines or recommendations for classification of students based on their answers to measures of SWB and distress in the context of school-based, universal mental health screening. This dissertation includes two studies designed to further the field of DCM by exploring two approaches to mental health classification among high school students following universal mental health screening. Study 1 investigated classification of students' mental health on two measures of SWB and distress. Using Receiver Operating Characteristic curve analyses, optimal cut scores on both measures of DCM mental health were identified. Students were classified into groups based on these cut scores, and outcomes of positive youth development were significantly different across groups. All differences favored students with the highest scores on SWB and lowest scores on distress. In Study 2, latent profile analysis was carried out on two subsamples to explore empirically-based latent classes of DCM mental health

among students in an effort to identify possible cut scores on measures of SWB and distress. Fit information did not indicate a best fitting model that could be replicated to further recommendations for school-based screening. Implications for school-based universal DCM screening are discussed.

*Keywords:* dual-continua model, adolescents, screening, classification

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# Exploration of Two Alternative Approaches to Dual-Continua Mental Health Classification among High School Students

## **Introduction**

Adolescent mental health in the United States is of increasing concern, with approximately half of all lifetime mental health conditions beginning by adolescence (Kessler et al., 2007). In 2010, the Center for Disease Control and Prevention (CDC) found suicide to be the second leading cause of death for youths and young adults between 10 and 24 years of age. One-time prevalence estimates of mental health disorders among youths have ranged from 13% (Center for Disease Control and Prevention, 2013) to 40.3% when including anxiety, mood, behavior, substance use, and eating disorders (Kessler et al., 2012). Despite prevalence estimates, only 20% to 45% of youths with mental health problems receive timely services (Costello, He, Sampson, Kessler, & Merikangas, 2014; National Institute of Mental Health, 2009). Frequently, symptoms of mental health problems are first noticed in youths' school settings (Richardson, Morissette, & Zucker, 2012). Considering the many barriers to accessing mental health care, including lack of health care coverage and difficulty with financially affording services, schools have the potential to provide social, emotional, and behavioral health services to all youths (Substance Abuse and Mental Health Services Administration, 2012).

Currently, schools are the most common providers of mental health services for youths (Costello et al., 2014; Green et al., 2013). In a national study of adolescent students from 320 schools in the United States ( $N = 4,445$  adolescent-parent pairs), 56% of adolescents with a mental health disorder received services through their schools (Green et al., 2013). For those students with mild-to-moderate mental disorders, service utilization was

positively associated with their schools' engagement in early identification strategies, such as school-based mental health screening. Thus, youths were more open to services for social-emotional challenges if their schools normalized mental health problems and promoted a climate of acceptance and care through early identification interventions. Despite encouraging findings for school-based prevention and early identification strategies, Connors, Arora, Curtis, and Stephan (2015) found that only 25% of school mental health practitioners utilized evidence-based mental health assessment and screening to address the social-emotional needs of students, while 80% utilized academic data (e.g., grades, attendance, and office discipline referrals). Although academic data are one part of a comprehensive story of a student's functioning, utilizing these methods alone can lead to the under-identification of students who are experiencing internalizing, rather than externalizing, symptoms of distress (Bruhn, Lane, & Hirsch, 2013).

Contemporary literature on school-based mental health advocates for mitigation of social-emotional problems and promotion of wellness through universal mental health screening that asks students about symptoms of distress and subjective wellbeing (SWB; Dowdy et al., 2015; Moore et al., 2015). A balanced approach to screening in which students are asked about quality of life and wellbeing in addition to distress is imperative, because only 15% to 20% of students report experiencing social-emotional difficulties at one time (Furlong et al., 2018; Kim, Furlong, Dowdy, & Felix, 2014). By asking questions that are meaningful to all students, schools can make informed decisions to promote wellbeing. Youths' SWB is positively associated with social-emotional strengths (Furlong, You, Renshaw, Smith, & O'Malley, 2014), prosocial behaviors, quality of interpersonal relationships, and good physical health (Lyubomirsky, King, & Deiner, 2005). Although the

value of asking youths about symptoms of wellness and distress has been investigated, research must explore methods of classification of students based on self-reported distress and SWB to inform practical cut scores that can be applied within the context of schoolwide mental health screening. The current studies aimed to explore two approaches to classification of students into mental health groups based on responses to measures of distress and SWB.

### **Dual-Continua Model of Mental Health**

The dual-continua, or dual-factor, model (DCM; Greenspoon & Saklofske, 2001) of mental health offers a framework for conceptualizing youths' mental health as not only the absence of psychological distress, but the presence of indicators of enhanced youth development and wellbeing. Thus, the absence of distress does not imply mental health (Keyes, 2007). When applied within a mental health screening context, the DCM has the potential to provide schools with information for prevention and early intervention practices that cannot be gleaned from data on students' academic and social-emotional problems alone. For example, despite reported levels of distress, higher SWB among adolescents has been associated with more self-worth (Greenspoon & Saklofske, 2001) and social-emotional strengths (Moore, 2017; Rebelez-Ernst, 2015), a greater sense of school connectedness (Antaramian et al., 2010; Lyon et al., 2012; Moffa, Dowdy, & Furlong, 2016), and higher academic achievement (Antaramian et al., 2010; Suldo et al., 2016). Additionally, low SWB has been associated with fewer social supports and worse scholastic competence than students reporting higher SWB, even for those also reporting low levels of distress (Greenspoon & Saklofske, 2001).

Previous applications of the DCM to school-based mental health screening have focused on demonstrating the value of asking individuals about SWB and distress by examining student outcomes based on levels of both constructs. In this pursuit, these studies have logically formed groups of students based on self-reported distress and SWB. Suldo and Shaffer (2008), for example, created four groups based on population-based and sample-specific norms on measures of SWB and distress: (a) *complete mental health* (high SWB and low pathology), (b) *vulnerable* (low SWB and low pathology), (c) *symptomatic but content* (high SWB and high pathology), and (d) *troubled* (low SWB and high pathology). As there is no agreed upon method for classification of students into DCM groups, criteria have previously been based on rational cut scores or sample-specific distributions. While this approach to classification could be replicated by school practitioners conducting mental health screening, it also presents several issues that future research should address. Sample-specific distributions of SWB and distress will vary, suggesting that otherwise similar individuals could be classified into different mental health groups based on the sample-specific distribution of scores. Grouping students based on a normal distribution also creates difficulty when tracking the overall mental health of the student body and individual students over time, because the proportion of students in each group will align with a normative curve, unless the sample distribution is markedly different than the national normative group.

Recently, research has used Latent Profile Analysis (LPA) as an alternative approach to better understanding youths' DCM mental health (Kim, Dowdy, Furlong, & You, 2016; Moore, 2017; Rebelez-Ernst, 2015). Rather than applying logical cut scores, the LPA approach creates groups, or latent classes, based on underlying response patterns to measures of DCM (Masyn, 2013; Nylund, Bellmore, Nishina, & Graham, 2007). Although LPA offers

a promising empirically-based approach to better understanding students' DCM mental health, it has not been examined as an approach to classification that can be practically applied in the school setting. More research is needed to examine if LPA is an appropriate approach to inform cut scores on measures of DCM with youths.

### **The Current Studies**

While DCM research continues to demonstrate the value in assessing for students' SWB and distress, there is a need for research to develop optimal cut scores that can be applied to measures of SWB and distress by school practitioners conducting universal DCM screening. The present studies (Study 1 and Study 2) explored two possible approaches to DCM classification as a first step in making DCM screening practical, feasible, and useful for schools. Both studies were conducted using the same large, heterogeneous sample of high school students to increase generalizability of these approaches for future school-based DCM screening.

Study 1 explored an alternative cut-score approach to classification based on measures of SWB and distress. Cut-score approaches to classification can help facilitate school teams' efforts to independently implement screening practices, provide follow-up services, and promote wellness for all students. Receiver operating characteristic (ROC) curve analysis was conducted to identify students who are doing well (termed *flourishing*) and students who are not doing well (termed *languishing*; Keyes, 2005) based on measures of SWB and distress. This type of analysis has not been previously applied in the context of dual-continua mental health screening but has the potential to identify optimal cut scores on DCM measures for use by school practitioners.



Study 2 sought to identify latent profiles of DCM mental health among high school students that could inform empirically-based cut scores on the same measures of DCM utilized in Study 1. As previous research findings indicate inconsistencies in the number of optimal classes and methodology for specifying indicators of SWB and distress, Study 2 also investigated the generalizability of previously identified empirically-based DCM classes on the proposed sample of students. The current studies sought to examine two approaches to developing accurate and appropriate cut scores on measures of SWB and distress to be applied in the school setting. With better methods of classification, school practitioners and staff can make informed decisions about schoolwide and targeted strategies to promote student wellness and address risk of negative outcomes.

**Study 1: Exploring an Alternative Approach to Dual-Continua Mental Health  
Classification among High School Students**

## Abstract

Contemporary research on students' mental health has emphasized the importance of the dual-continua model of mental health, which considers wellbeing and distress to be separate constructs that uniquely contribute to one's overall mental health. Although recent literature has investigated the value of including measures of wellbeing and distress in school-based screening, there are currently no universally accepted criteria for determining which students are doing well (i.e., *flourishing*) and which need additional services (i.e., *languishing*). The current study explored classification of students' mental health based on optimal cut scores derived from a series of Receiver Operating Characteristic curve analyses. A sample of high school students ( $N = 4,398$ ) from five high schools in California reported on their subjective wellbeing and distress as part of survey administration in the fall of 2017. Differences across mental health groups were examined based on responses to questions related to social-emotional, behavioral, and academic outcomes. Significant and meaningful differences across mental health groups were found, suggesting that the selected cut scores on measures of subjective wellbeing and distress have the potential to be useful for classification and resulting follow-up care in the context of school-based universal mental health screening. Further evidence was found for the utility of a dual-continua approach to youths' mental health.

*Keywords:* dual-continua model, flourishing mental health, adolescents

## **Exploring an Alternative Approach to Dual-Continua Mental Health Classification among High School Students**

In the United States, it is estimated that as few as 36% of youth with a mental health disorder receive treatment (Merikangas et al., 2011). Given the numerous barriers to accessing mental health resources for youth and families, including stigma, healthcare coverage, and financial costs (Substance Abuse and Mental Health Services Administration, 2012), schools offer an accessible means through which youth can receive mental health support and benefit from early prevention and intervention strategies (Manassis et al., 2010; Manion, Short, & Ferguson, 2013). Previous research has shown that youth are more likely to seek mental health services through their schools than any other system of care (Slade, 2002). Following comprehensive school-based mental health services, students have demonstrated improvement in prosocial behaviors and fewer mental health difficulties (Walter et al., 2011). While schools have put forth efforts to identify students who are struggling with mental health concerns, traditional methods of identification and referral, such as teacher referrals and office discipline referrals (ODR), are unreliable, particularly for students who primarily experience symptoms of internalizing distress, such as depressed and anxious emotionality (Bruhn, Lane, & Hirsch, 2013).

School-based universal mental health screening offers an alternative to traditional referral methods, potentially giving schools the ability to proactively support students experiencing distress. Despite the potential benefits, it has been estimated that approximately 13% of schools carry out schoolwide emotional and behavioral screening (Bruhn, Woods-Groves, & Huddle, 2014), with deficit-based screening as the focus of most schools' efforts (Dowdy et al., 2015). Deficit-based screening, with its focus on social, emotional, and

behavioral problems, does not allow school teams to formulate comprehensive pictures of how *all* students are doing, but rather provides information about the estimated 15% to 20% of students who are experiencing difficulties at the time of screening (Kim, Furlong, Dowdy, & Felix, 2014). To address this issue, contemporary research has examined if asking questions about students' subjective wellbeing (SWB), or their feelings about and appraisal of their lives, provides expanded information for all students (Keyes, 2006a, 2006b; Moore et al., 2015). While most students do not engage in antisocial behaviors or experience significant, lasting distress symptoms — the focus of problem-based screening — quality of life and wellbeing information is meaningful for all students (Furlong et al., 2018). Although recent literature has investigated the value of including measures of wellbeing and distress in school-based screening, there are currently no established criteria for determining which students are doing well, not doing well, or somewhere in between based on responses to these measures. Therefore, applying research on school-based universal mental health screening to practice is currently difficult and seemingly impractical for practitioners. The current study explored an alternative approach to classification of students' mental health based on measures of SWB and distress to better inform future school-based universal screening practices.

### **Assessment of Subjective Wellbeing**

Proponents of assessing youths' wellbeing have argued that ameliorating symptoms of distress alone does not guarantee that an individual will experience full mental health (Keyes, 2007). Instead of a pathogenic-centric approach to mental health, in which health is the absence of disease, a two-continua model proposes that mental health encompasses both the absence, or mitigation, of psychopathology and the presence of positive functioning or

SWB (Keyes, 2005, 2007). Previous research has found that youths' SWB is associated with important social-emotional and academic indicators of positive youth development above and beyond symptoms of distress (Antaramian, Huebner, Hills, & Valois, 2010; Greenspoon & Saklofske, 2001; Lyons, Huebner, Hills, & Shinkareva, 2012; Moffa, Dowdy, & Furlong, 2016; Moore, 2017; Suldo & Shaffer, 2008; Suldo, Talji-Raitano, Kiefer, & Ferron, 2016). Youths' SWB is positively associated with youths' covitality, or the presence of multiple strengths and assets indicative of enhanced youth development (Furlong, You, Renshaw, Smith, & O'Malley, 2014), prosocial behaviors, strong interpersonal relationships, and good physical health (Lyubomirsky, King, & Diener, 2005).

Keyes' model of flourishing mental health is one of several that prioritizes the presence of wellness and symptoms of positive mental health (Keyes, 2002). The model defines SWB as the presence of emotional, social, and psychological wellbeing, with classification based on individuals' self-report of experiences falling within each of the three separate wellbeing constructs (Keyes, 2005). Emotional (hedonic) wellbeing includes the presence of positive and negative affect and overall life satisfaction (Keyes, Shmotkin, & Ryff, 2002). Social wellbeing captures individuals' experiences in social situations (Keyes, 1998), while psychological wellbeing captures individuals' perspectives of their development and functioning (Ryff & Keyes, 1995). Together, psychological and social wellbeing make up eudaimonic wellbeing, or positive social functioning (Keyes, 1998; Ryff & Keyes, 1995).

Keyes' model of SWB is operationalized by the *Mental Health Continuum-Long Form* and *-Short Form* (Keyes, 2002), which measures three factors of SWB: *Emotional*, *Social*, and *Psychological Wellbeing*. The three-factor structure of the instrument has demonstrated good model fit with a sample of school-aged youth ( $N = 2,907$ ), with modestly

strong correlations between factors (Keyes, 2006b). Additionally, these constructs were strongly positively correlated with measures of global self-concept, determination, and school connectedness and modestly negatively correlated with symptoms of depression (Keyes, 2006b). Keyes' model of mental health classifies individuals in a similar manner to the Diagnostic and Statistical Manual of Mental Disorders (DSM)-IV approach for major depressive episode (Keyes, 2006b). Specifically, individuals are classified as *flourishing*, *moderately mentally healthy*, or *languishing*. According to Keyes, *flourishing* mental health is defined by the presence of emotional wellbeing and positive social functioning, while *languishing* mental health is defined by the absence of mental health (Keyes, 2002).

Individuals who do not fall into either group (i.e., report some symptoms of positive mental health) are classified as *moderately mentally healthy*. Youth who are *flourishing* have reported higher levels of psychosocial functioning and fewer symptoms of depression and conduct problems than peers classified as *moderately mentally healthy* and *languishing* (Keyes, 2006b). Among youth ages 5-18 years, Keyes (2006a) found that on average, youth reported experiencing emotional wellbeing "almost every day," psychological wellbeing "2-3 times a week," and social wellbeing "about once a week." Prevalence of mental health among adolescents ( $N = 1,284$ ) has indicated most youth, ages 12 to 18, are *moderately mentally healthy* (55.9%), then *flourishing* (37.9%), and finally *languishing* (6.2%; Keyes, 2006a). These results suggest that most youth do not experience *flourishing* mental health.

Coupled with findings that *flourishing* youth are less likely to report symptoms of depression and conduct problems, including arrest and substance use, and more likely to endorse high levels of self-concept, self-determination, and quality of relationships than *moderately mentally healthy* and *languishing* youth (Keyes, 2006a), it is important that school-based

screening for mental health consider youths' subjective wellbeing and mental health, as well as distress.

### **Dual-Continua Approach to Mental Health Screening**

While indicators of mental health and wellbeing are paramount to understanding how to promote flourishing at an individual and schoolwide level, schools must also identify students at-risk for mental health concerns. A balanced, multi-component approach to school-based mental health screening better equips schools to promote students' mental health while also treating symptoms associated with negative outcomes (Furlong et al., 2018). The dual-continua, or dual-factor, model (DCM; Greenspoon & Saklofske, 2001), also called a bi-dimensional model of mental health (Renshaw & Bolognino, 2017), offers a framework with which to measure youths' mental health, because it conceptualizes SWB and symptomatology as two separate, but related constructs that encompass mental health. Applied within a universal screening context, the DCM offers schools a tool with which to implement early intervention and prevention practices that are not afforded by symptom-focused strategies using deficit-based screening.

Research that has applied the DCM to assessment of adolescents' mental health has classified groups of adolescents and applied labels based on self-reported SWB and distress. While measures used to classify students have varied, each study has employed at least one measure of wellness and one measure of distress. Results across studies with adolescents have suggested that there are meaningful differences across groups based on both distress and SWB. For example, Moore (2017) found that ninth- and eleventh-grade students who reported high levels of SWB and low levels of distress (i.e., *complete mental health*) reported significantly higher levels of co-occurring strengths and SWB than students who reported



high levels of SWB and distress (i.e., *symptomatic but content*) and students who reported low levels of SWB and high levels of distress (i.e., *troubled*; Moore, 2017). Adolescents' levels of SWB have also been found to be positively associated with school connectedness and belonging (Antaramian et al., 2010; Lyons et al., 2012; Moffa et al., 2016), with students classified into the *complete mental health* and *symptomatic but content* groups reporting significantly higher levels of school connectedness than peers in the *troubled* and *vulnerable* (i.e., low levels of SWB and distress) groups. Youth falling in the *complete mental health* group have also reported significantly higher academic performance, including GPA and academic self-perceptions (Antaramian et al., 2010; Moore, 2017; Rebelez-Ernst, 2015; Suldo & Shaffer, 2008; Suldo et al., 2016). Together, these studies emphasize the importance of attending to both SWB and distress, because outcomes differ based on the presence of both.

### **DCM Classification Approaches**

Within the context of school-based universal screening, a classification algorithm is required to identify which youths are sufficiently at-risk to merit follow-up and to better understand which external conditions and internal characteristics contribute to wellness. Contemporary screening literature emphasizes the value of measuring both students SWB and distress; however, there is currently no universally accepted algorithm for screening classification, which causes confusion for practitioners. Moreover, schools might elect to forego universal DCM screening due to hesitation they will not have the bandwidth to classify students or the resources to care for every student in need. Advances in DCM screening require research that addresses these barriers by examining classification algorithms that are feasible and meaningful. Previously, students have been classified based

on published and local, sample-specific norms (e.g.,  $T$  scores  $> 60$ ,  $z$  scores  $> 1.00$ ; Antaramian et al., 2010; Kelly, Hills, Huebner, & McQuillin, 2012; Suldo & Shaffer, 2008; Suldo et al., 2016). For instance, middle school students ( $N = 500$ ) were classified into four groups based on students' self-reports of SWB and pathology (Suldo et al., 2016). Subjective wellbeing was measured by responses on the *Students' Life Satisfaction Scale* (SLSS; Huebner, 1991) and *Positive and Negative Affect Scale for Children* (PANAS-C; Laurent et al., 1999), while internalizing and externalizing symptoms of distress were assessed with the internalizing composite of the *Self-Report of Personality* form (SRP) of the *Behavior Assessment System for Children, Second Edition* (BASC-2; Reynolds & Kamphaus, 2004) and the *BASC-2 Teacher Rating Scale* (TRS; Reynolds & Kamphaus, 2004). Students' levels of distress were evaluated based on published norms, in which  $T$  scores of 60 or above on either BASC-2 rating scale (i.e., SRP or TRS) indicated a high level of pathology. SWB was classified based on the proportion of students classified as high and low pathology based on sample-specific  $z$  scores. Since 30% of students had  $T$  scores of 60 or higher on the BASC-2 rating scales, logical cut scores on standardized scores ( $z$  scores) of the SLSS and PANAS-C were used to differentiate the bottom 30% of SWB.  $Z$  scores on the SLSS and positive affect scale of the PANAS-C were summed, then  $z$  scores on the negative affect scale of the PANAS-C were subtracted to calculate a SWB score. The binary pathology and SWB classifications were crossed to form four DCM groups.

Classification based on the above approach presents several issues. First, levels of SWB are likely more complex than "high" and "low," and it is probable that someone with a SWB score in the 31<sup>st</sup> percentile does not have optimal levels of SWB. Furthermore, mean scores for SWB vary across samples, meaning that otherwise similar individuals classified as

having *complete mental health* in some studies could fall into the *vulnerable* group in studies with higher cut criteria if sample specific norms are used to create cut scores (Antaramian et al., 2010; Kelly et al., 2012; Suldo & Shaffer, 2008; Suldo et al., 2016). Additionally, classification based on published and local norms creates difficulties when following students longitudinally, as the proportion of students in each group will coincide with a normative curve even if the overall health of the student body improves over time. Finally, the combined severity of scores on SWB and distress measures is not considered, which can lead to false assumptions about students' mental health. For instance, a *T* score of 60 or higher on either externalizing or internalizing distress measures would classify an individual as experiencing high distress, but a *T* score of 57-59 on both internalizing and externalizing symptoms of distress would be categorized as normative distress even if an individual with these scores is likely to be experiencing higher distress. Utilizing this classification method could lead to under identification of students in distress.

### **An Alternative Classification Approach**

Although universal screening is a critical component of intervention and prevention efforts within schools, it is possible that it has not been widely adopted in part due to the complexity of existing recommendations for classifying students based on wellness and distress. Currently, there are no uniform guidelines or approaches to classifying students following a screening within the DCM approach. The goal of school-based universal screening is to conduct an initial assessment of students' needs that is inexpensive and time efficient (Smith, McCarthy, & Anderson, 2000). Therefore, accurate systems for classifying students in need of follow-up services, as well as students who are doing well, are needed (Yovanoff & Squires, 2006). When making decisions concerning classification, schools must

consider the impact of screening on students and families, resources available for follow-up services, and the consequences of missing students at-risk for social-emotional problems (Yovanoff & Squires, 2006). A cut-score approach, in which a specific score indicates the need for follow-up, offers a way for schools to independently carry out screening, provide subsequent care, and promote the wellbeing of all students. However, identifying the optimal cut score depends on the measures and context of the screening. Yovanoff and Squires (2006) advise that optimal cut scores should be based on the classification error rates due to the sample and measures, as well as the costs associated with false positive and false negative results.

A criterion approach to classification using receiver operating characteristic (ROC) curves offers a classification alternative to norm-based approaches by identifying optimal cut scores on a measure based on an existing diagnosis or dichotomous outcome. ROC curve analysis can evaluate several possible cut scores at one time and can be used to classify individuals even when the score distribution is non-normal (DiStefano & Morgan, 2011). In a comparison of classification approaches to identify youth ( $N = 2,459$ , 6-11 years old) with social, emotional, and behavioral difficulties, DiStefano and Morgan (2011) found that standardized scores (e.g.,  $T$  scores) did not produce accurate classification compared to ROC curve analysis. Although ROC curve analysis is a common approach to mental health screening when identifying symptomatology consistent with mental disorders among youth (e.g., DiStefano & Morgan, 2011; Kilgus, Tylor, & von, 2018; Youngstrom, 2013), this approach has never been attempted in the context of school-based dual-continua mental health screening. However, as evidence mounts for taking a DCM approach to youths' mental health, implementation of universal screening with measures of both wellness and

distress will be dependent on guidance regarding classification approaches that are useful and meaningful to schools. It is possible that ROC curve analysis can aid in identifying optimal cut scores on measures of SWB and distress, which might provide a plausible way for schools to carry out universal DCM screening.

### **The Current Study**

The current study explored the utility of ROC curve analysis to explore an alternative approach to classification that might be useful within the school setting. Classification was based on students' positive mental health "diagnosis" from Keyes' model of *flourishing* mental health, as the goal is to help students be *well*. Cut scores were examined on one measure of SWB and one measure of distress to classify students as *flourishing* or *not flourishing* and *languishing* or *not languishing*. These are the two groups of students that universal screening aims to differentiate when identifying students that are least (*flourishing*) and most (*languishing*) likely to need immediate follow-up services. By knowing who is *flourishing*, schools can glean more information about pathways to wellness, correlates to wellness, and who is likely to show resilience in the face of adversities. Students who do not fall into these two groups (i.e., *flourishing* or *languishing*) are classified as *moderately mentally healthy*. Furthermore, mean scores on measures of social-emotional strengths, school connectedness, overall life satisfaction, depressed emotionality, and self-reported grades were investigated for students in all three mental health groups (i.e., *flourishing*, *moderately mentally healthy*, and *languishing*). By examining differences across groups, a better understanding of the utility of this classification approach was gained. Covariates were chosen based on previous literature that has examined associations between dual-continua mental health and indicators of positive youth development (Antaramian et al., 2010; Moffa,

Dowdy, & Furlong, 2016; Moore, 2017). Consistent with a DCM approach to assessment in which both SWB and distress are measured, the current study sought to answer the following research questions:

RQ1: What are the optimal cut scores on measures of SWB and distress to predict *flourishing* and *languishing* mental health among a subsample of high school students based on ROC curve analyses? Do the optimal cut scores selected demonstrate cross validation with a different subsample of high school students?

RQ2: Do mental health groups formed based on optimal cut scores differ on social-emotional strengths, school connectedness, overall life satisfaction, depressed emotionality, and self-reported grades?

## Method

### Participants

Participants were a cross-sectional sample of high school students (Grades 9 through 12) from five public high schools in five different school districts in California ( $N = 4,398$ ). For the purposes of the current study design, a split-sample design was implemented to assess the validity of cut scores identified in approximately 50% of the sample (i.e., calibration sample) with the other 50% of the sample (i.e., validation sample).

**Calibration subsample.** The calibration sample included participants ( $n = 2,209$ ) from five schools in California, with 24.9% ( $n = 549$ ) of students reporting they were in ninth grade, 24.9% ( $n = 551$ ) in tenth grade, 29.0% ( $n = 641$ ) in eleventh grade, 20.9% ( $n = 462$ ) in twelfth grade, and 0.3% ( $n = 6$ ) who reported “other,” “ungraded,” or did not include this information. Approximately 51% of participants identified as female and almost 49% as male. Students’ self-reported race was as follows: 38.7% ( $n = 855$ ) White, 37.7% ( $n = 833$ ) two or more races, 10.4% ( $n = 230$ ) Asian, 2.6% ( $n = 58$ ) American Indian or Alaska Native,

1.9% ( $n = 42$ ) Black or African American, 1.4% ( $n = 30$ ) Native Hawaiian or Pacific Islander, and 7.3% ( $n = 161$ ) did not report this information. Approximately 46% ( $n = 1,009$ ) of students in the sample identified as Hispanic, and 39.2% ( $n = 866$ ) of the sample indicated that they receive free or reduced-priced lunches at school.

**Validation subsample.** The validation sample consists of 2,189 students from the same five schools as students in the calibration sample. Approximately 53% ( $n = 1,152$ ) of students identified as female and 47% ( $n = 1,019$ ) as male. The sample consisted of 25.4% ( $n = 555$ ) ninth grade students, 23.1% ( $n = 506$ ) tenth grade students, 29.1% ( $n = 636$ ) eleventh grade students, 22.1% ( $n = 483$ ) twelfth grade students, and 0.3% ( $n = 9$ ) who reported “other,” “ungraded,” or did not include this information. Students self-reported their race as follows: 38.4% ( $n = 840$ ) White, 35.2% ( $n = 770$ ) two or more races, 10.9% ( $n = 239$ ) Asian, 4.5% ( $n = 98$ ) American Indian or Alaska Native, 3.1% ( $n = 67$ ) Black or African American, 1.6% ( $n = 36$ ) Native Hawaiian or Pacific Islander, and 6.3% ( $n = 139$ ) did not report this information. Approximately 44% ( $n = 964$ ) of students identified as Hispanic. Based on student self-report, 37.6% ( $n = 824$ ) reported receiving free or reduced-price lunches at school.

### **Dual-Continua Mental Health Measures**

To be consistent with the DCM approach to assessing for mental health, a measure of SWB and a measure of distress were administered to youth. While it is most important that both constructs are included when conceptualizing youths’ mental health, the current study acknowledges that measures used to assess these constructs have varied in the literature.

**Subjective wellbeing.** Students’ SWB was measured based on a total score on the *Brief Multidimensional Student’s Life Satisfaction Scale* (BMSLSS; Seligson, Huebner, &

Valois, 2003), a five-item self-report measure of students' satisfaction with various aspects of life. Students are asked to describe their satisfaction with their family life, friendships, school experience, self, and where they live on a six-point scale (1 = *very dissatisfied*, 2 = *dissatisfied*, 3 = *somewhat dissatisfied*, 4 = *somewhat satisfied*, 5 = *satisfied*, and 6 = *very satisfied*). Total scores were summed from responses on each of the five items (range 5 – 30). A one-factor structure has been supported by confirmatory factor analysis, with fit statistics indicating adequate model fit and strong loadings (.53-.79; Seligson et al., 2003; Seligson et al., 2005; McDougall, Wright, Nichols, & Miller, 2013; Ng, Huebner, Maydeu-Olivares, & Hills, 2017). The BMSLSS has been found to have acceptable internal consistency with adolescents ( $\alpha = .75-.83$ ; Funk, Huebner, & Valois, 2006; Ng et al., 2017; Zullig, Valois, Huebner, Oelmann, & Drane, 2001). Longitudinal measurement invariance across a one-year period was confirmed for an adolescent sample (Ng et al., 2017). For the calibration and validation subsamples, internal consistency was strong,  $\alpha = .81$ .

**Distress.** Distress was measured by a total score from the *Social Emotional Distress Survey – Secondary* (SEDS-S; Dowdy, Furlong, Nylund-Gibson, Moore, & Moffa, 2018), a 10-item self-report measure used to gauge students' feelings of distress, including experiences of anxious and depressed emotionality. Items ask students to rate the degree to which they have experienced symptoms of distress in the past month (e.g., *In the past month, it was hard to get excited about anything*). Responses are on a four-point scale, 1 = *not at all true*, 2 = *somewhat true*, 3 = *pretty much true*, and 4 = *very true*. Total scores were summed from responses on the ten items (range 10 – 40). Randomly generated split-sample exploratory and confirmatory factor analyses with two independent samples of high school students have supported adequate fit for a one-factor model and convergent and discriminant validity



(Dowdy et al., 2018). The internal consistency reliability estimates for the calibration and validation subsamples were excellent,  $\alpha = .92$ .

### **Criterion Measure**

**Mental health.** Positive mental health diagnoses based on item responses to the *Mental Health Continuum – Short Form* (MHC-SF; Keyes, 2005) were used as the criterion for ROC curve analyses. While measures of symptomatology are more common as the criterion measures, or “gold standards,” of mental health against which cut scores are compared, the current study prioritized positive mental health consistent with the goal of promoting students’ wellness, rather than only minimizing symptoms of distress. Participants were classified as experiencing *flourishing*, *moderate*, and *languishing* mental health based on responses on the MHC-SF. The MHC-SF is a brief measure of positive mental health, including psychological, emotional, and social wellbeing, adapted from the *MHC – Long Form* (MHC-LF; Keyes, 2002). The MHC-LF was developed based on the conceptualization of mental health as the presence of pleasure (hedonic wellbeing) and psychological functioning (eudaimonic wellbeing; Keyes, 2002). In contrast to the 40-item MHC-LF, the MHC-SF consists of 14 items: three items measuring emotional wellbeing, six measuring psychological wellbeing, and five measuring social wellbeing. A three-factor correlated model has been supported among youth, ages 12-18 (Keyes, 2006a). Individuals are asked the frequency with which they experienced each symptom of wellbeing during the past month. Item response options include 0 = *never*, 1 = *once or twice*, 2 = *about once a week*, 3 = *2 or 3 times a week*, 4 = *almost every day*, and 5 = *every day*. Based on item responses, individuals are diagnosed with *flourishing*, *moderate*, or *languishing* mental health. Following recommendations from Keyes (2005), participants in the current study were

classified as experiencing *flourishing* mental health if they reported feeling one of the three indicators of emotional (i.e., hedonic) wellbeing and at least six of the 11 indicators of psychological and social wellbeing (i.e., positive functioning) “every day” or “almost every day.” Participants were classified as *languishing* mental health if they responded “never” or “once or twice” on at least one indicator of emotional wellbeing and at least six indicators of psychological and social wellbeing. All other response patterns fell under the criteria of *moderately mentally healthy*. For the calibration subsample, internal consistency for *emotional wellbeing*, *psychological wellbeing*, and *social wellbeing* was  $\alpha = .89, .90, \text{ and } .92$ , respectively. For the validation subsample, internal consistency for the above subscales was  $\alpha = .90, .90, \text{ and } .93$ , respectively.

### **Social-Emotional and Educational Covariates**

**Social-emotional.** The co-occurrence of multiple social-emotional strengths, termed *covitality*, was assessed by the *Social Emotional Health Survey – Secondary* (SEHS-S; Furlong, You, Renshaw, Smith, & O’Malley, 2014), a 36-item self-report measure. The current study utilized students’ mean score on the 36 items as an outcome measure of students’ social emotional strengths according to mental health groups based on ROC analyses. Students rated the degree to which they could relate to statements about their strengths on a four-point scale (1 = *not at all true*, 2 = *somewhat true*, 3 = *pretty much true*, and 4 = *very much true*). Confirmatory factor analyses and invariance testing across multiple groups have supported a higher-order factor structure with 12 individual strengths loading onto four second-order traits of *Belief-in-Self*, *Belief-in-Others*, *Emotional Competence*, and *Engaged Living* (You, Furlong, Felix, & Furlong, 2015). These four constructs measure an overall higher-order factor termed *Covitality*. According to Furlong and colleagues (2014),

*Covitality* has been found to positively predict SWB and self-reported grade point average and has been found to be negatively associated with symptoms of distress. For the both subsamples, the internal consistency of the 36 items was excellent,  $\alpha = .94$ .

To assess life satisfaction, item responses to one question about students' overall life satisfaction were examined across mental health groups. Students were asked to rate their satisfaction with their life on a scale of 0 = *dissatisfied* to 100 = *satisfied*. To assess distress, responses to an item measuring the occurrence of depressed emotionality were also investigated across groups, with students answering "no" (value = 1) or "yes" (value = 2) to the question, "In the past 12 months, did you ever feel so sad or hopeless almost every day for two weeks or more that you stopped doing some usual activities?"

**Educational.** To assess school connectedness, items from the California Healthy Kids Survey (CHKS; CHKS, 1999) measured students' self-reported sense of connectedness to school (McNeely, Nonnemaker, & Blum, 2002; Resnick et al., 1997). Students' sense of school connectedness was measured by a mean score on five items on a five-point scale (1 = *strongly disagree* to 5 = *strongly agree*). Items included, "I feel close to people at this school," "I feel like I am part of this school," "I am happy to be at this school," "The teachers at this school treat students fairly," and "I feel safe at my school" (Resnick et al., 1997). A unidimensional factor structure and invariance across multiple sociocultural groups have been supported with adolescents (Anderman, 2002; Furlong, O'Brennan, & You, 2011). Internal consistency for the calibration and validation samples was good,  $\alpha = .83$  and  $\alpha = .83$ , respectively.

To assess academic achievement, students' overall description of their course grades was measured with one item. Item responses were measured on an eight-point response scale

(8 = Mostly A's, 7 = Mostly A's and B's, 6 = Mostly B's, 5 = Mostly B's and C's, 4 = Mostly C's, 3 = Mostly C's and D's, 2 = Mostly D's, and 1 = Mostly F's).

## **Procedure**

In the beginning of the 2017/2018 school year, as part of a grant investigating social-emotional health (Institute of Education Sciences Grant #R305A160157), high school students from five high schools in Northern and Southern California participated in anonymous survey administration as part of the existing CHKS administration process conducted by WestEd. High schools were randomly selected based on size and region, and the five high schools in the current study were the first to elect to administer the CHKS with the BMSLSS, SEDS-S, SEHS, and other social-emotional information. The survey was electronically offered in English and Spanish. Information was collected on self-reported gender, race/ethnicity, language classification status (i.e., English Language Learner), home language, and eligibility for free/reduced lunch. Students were required to have passive consent from their parents or caregivers to participate.

## **Data Analysis Plan**

**Missing Data Analysis.** Prior to data analyses, a missing data analysis was performed to investigate patterns of missing data. First, cases were removed that met the criteria for rejection by the CHKS ( $n = 36$ ). These criteria include inconsistencies in alcohol or drug use, fictitious drug use, and dishonesty (i.e., respondents who answered they responded to some or hardly any survey questions honestly). With the remaining cases, Little's test to determine if missing data were missing completely at random (MCAR) was carried out, indicating that data were not MCAR. However, further missing value analyses indicated that missing data were likely missing at random (MAR), with no apparent relation between whether the data

were missing and the missing data. Thus, cases were included in further analyses if all items of the BMSLSS and SEDS were answered, enough items of the MHC-SF were answered to make a definitive positive mental health diagnosis (i.e., no fewer than 7 items), at least 80% of items on the SEHS-S and SCS were answered, and self-reported GPA was included. This resulted in a final sample of 4,398 participants (87% of entire sample retained, which was subsequently split into two subsamples).

**ROC Analyses.** Students' mental health was classified based on their responses to the *MHC-SF* (Keyes, 2006b) as *flourishing*, *moderately mentally healthy*, or *languishing*. ROC curve analyses using SPSS version 24.0 were utilized to examine the accuracy of measures of SWB (i.e., BMSLSS) and distress (i.e., SEDS-S) in predicting if students are *flourishing* or not and *languishing* or not (MHC-SF). Consistent with positive mental health diagnostic criteria on the MHC-SF, students who do not meet criteria for *flourishing* or *languishing* will be classified as *moderately mentally healthy*. First, ROC curve analyses were carried out with the calibration sample to identify optimal cut scores on the BMSLSS and SEDS-S. The area under the curve (AUC) was examined to evaluate the accuracy of both measures in predicting students who have *flourishing* and *languishing* mental health. AUC values indicated the likelihood that (a) a randomly selected student classified as *flourishing* had a higher total score on the BMSLSS than a randomly selected student classified as not flourishing, (b) a randomly selected student classified as *languishing* had a lower total score on the BMSLSS than a randomly selected student classified as not languishing, (c) a randomly selected student classified as *flourishing* had lower total score on the SEDS-S than a randomly selected student classified as not flourishing, and (d) a randomly selected student classified as *languishing* had a higher total score on the SEDS-S than a randomly selected

student classified as not languishing. Values for AUC range from .50 to 1.00, where .50 suggests a test is no better than random classification for predicting the desired outcome and 1.0 suggests that a test is perfect in predicting the outcome of interest. It is recommended that AUC values of .80 to .90 demonstrate good discrimination and values of .90 to 1.00 demonstrate excellent discrimination (Swets, 1996). Values of .70-.79 suggest fair discriminatory ability (Youngstrom, 2014). Further evidence for the accuracy of the test is supported if the AUC value is significant,  $p < .05$ .

Optimal cut scores for the measures of SWB (i.e., BMSLSS) and distress (i.e., SEDS-S) with the calibration sample were evaluated based on several criteria. Sensitivity and specificity estimates were calculated for all cut scores to determine the proportion of students with *flourishing* or *languishing* mental health who were detected by the BMSLSS and SEDS-S (i.e., sensitivity or true positive rate) and the proportion of students who were not *flourishing/languishing* who were not detected by the BMSLSS and SEDS-S (i.e., specificity or true negative rate). Glover and Albers (2007) recommended sensitivity and specificity to both be .75 or above. More recent literature on behavioral health screening suggested that sensitivity  $> .90$  is optimal,  $> .80$  is acceptable, and  $> .70$  borderline, while specificity  $> .80$  is optimal,  $> .70$  is acceptable, and  $> .60$  is borderline (Kilgus, Riley-Tillman, Chafouleas, Christ, & Welsh, 2014). As one of the goals of universal mental health screening is to identify all students in need of follow-up assessment and care, this study prioritized sensitivity and positive predictive power while aiming for acceptable specificity and recognizing that subsequent gates of assessment or screening might prioritize sensitivity and specificity equally (Stiffler & Dever, 2015). Therefore, only cut scores with sensitivity estimates of at least .75 were considered with the calibration sample. Although acceptable

specificity is  $> .70$ , borderline specificity ( $> .60$ ) will be considered if necessary to prioritize sensitivity  $> .75$ . Consistent with recent studies examining cut scores for school-based screening measures (i.e., Kilgus et al., 2018), cut scores that met these criteria and had the smallest difference between sensitivity and specificity estimates were selected with the intention of choosing cut scores with sensitivity and specificity as close to 1.00 as possible. Positive and negative predictive power and overall proportion correctly classified based on base rates for each mental health group were calculated for each cut score to differentiate both *flourishing/not flourishing* and *languishing/not languishing*. Once optimal cut scores were identified for both measures and both positive mental health diagnoses, sensitivity, specificity, and positive and negative predictive power of these cut scores were examined with the validation sample.

**Comparison of outcomes across groups.** A series of one-way between groups analysis of variance (ANOVA) with post-hoc tests were conducted using SPSS version 24.0 with the validation sample to examine significant differences in associated outcomes across groups of students identified as *flourishing*, *moderately mentally healthy*, and *languishing* by optimal cut scores. To be identified as *flourishing* or *languishing*, students met the optimal cut score on both the BMSLSS and SEDS-S, which is consistent with the assertion that mental health includes both the presence of wellness and absence of distress. Students who did not meet criteria for *flourishing* or *languishing* on both measures were classified as *moderately mentally healthy*. Mental health groups were compared on group means of social-emotional strengths, school connectedness, overall life satisfaction, depressed emotionality, and self-reported grades.

***Test of assumptions.*** Prior to analyses, data were checked for assumptions regarding normality, univariate outliers, and homogeneity of variance. Assumptions of normality for each outcome variable were assessed based on skewness and kurtosis values and the Kolmogorov-Smirnov test of normality, with non-significant tests indicating normality. Although assumption of normality was violated for each outcome, it is recommended that sample sizes of 30 participants and above move forward with analyses (Pallant, 2013), thus analyses proceeded as planned. Homogeneity of variance was assessed by Levene's test,  $p < .01$ , in which the null hypothesis is that the observed variances for each mental health group are equal for a given outcome (Tabachnick & Fidell, 2013). Since homogeneity of variance was violated, Welch and Brown-Forsythe tests of equality of means were reported to determine differences across groups instead of  $F$  ratios.

***Analysis of variance.*** Differences in outcome means across mental health groups were first evaluated by Welch and Brown-Forsythe tests of equality of means, in which significance values below .05 indicated significant differences between at least two mental health groups on the outcome of interest. If tests of significance for outcome variables suggested that there were significant differences between mental health groups, then post-hoc tests with Bonferroni correction using the Tukey HSD were performed to investigate which groups experienced significantly different outcome means. Effect size was measured by  $\eta^2$  values for each outcome variable. Values of .01 and above indicate a small effect size, .06 and above a moderate effect size, and .14 and above a large effect size (Cohen, 1988).

## **Results**

### **Descriptives**



Variable descriptive statistics and correlations were examined for both the calibration and validation subsamples (see Table 1). Base rates of positive mental health diagnoses were calculated. In the calibration subsample, 15.2% ( $n = 336$ ) of students met criteria for *languishing* mental health, 38.9% ( $n = 859$ ) met criteria for *moderately mentally healthy*, and 45.9% ( $n = 1,014$ ) met criteria for *flourishing* mental health. Similarly, base rates in the validation subsample were as follows: 15.6% ( $n = 342$ ) *languishing*, 38.3% ( $n = 839$ ) *moderately mentally healthy*, and 46% ( $n = 1008$ ) *flourishing*. These base rates are different than previous research with the MHC-SF with adolescents (i.e., Keyes, 2006a), which identified more than half of the sample as moderately mentally healthy.

**Cut scores.** ROC curve analyses were carried out with the calibration subsample ( $n = 2,209$ ) to determine optimal cut scores on the BMSLSS and SEDS-S to identify students with *flourishing*, *moderate*, and *languishing* mental health in the context of universal mental health screening. Table 2 provides a summary of all cut scores considered and AUC, sensitivity, specificity, and positive and NPVs. AUC values for the BMSLSS indicated that the measure has good discrimination value when identifying students who are *flourishing/languishing* and not *flourishing/languishing*. All cut scores that met the selection criteria are presented in Table 2. Based on requirements for sensitivity and specificity and the decision to prioritize PPV, a cut score of 23.5 (i.e., 24) and above on the BMSLSS was selected to classify individuals experiencing *flourishing* mental health. A cut score of 20.5 (i.e., 20) and below was selected to classify individuals experiencing *languishing* mental health. Sensitivity and specificity for both cut scores were in the acceptable range (see Table 2). Although PPV among possible cut scores was prioritized, all cut scores had higher NPVs than PPVs, indicating that these cut scores more accurately identify students who were not

*flourishing* or *languishing* than those who did meet the criteria for *flourishing* or *languishing* mental health according to the MHC-SF.

AUC values for the SEDS-S suggested that the measure had fair discriminatory value in identifying students who are *flourishing* (AUC = .752) and *languishing* (AUC = .766). ROC curve analyses indicated that only one cut score on the SEDS-S, a cut score of 20.5, had acceptable sensitivity and at least borderline specificity (i.e., SP > .60). Thus, scores of 21 and above were used to classify individuals as *flourishing*, and scores of 20 and below were implemented to classify individuals who were *languishing*. Like the BMSLSS, NPVs were above PPVs for both cut scores. Groups based on the optimal cut scores on each measure (see Table 2) were formed, with individuals meeting the cut score criteria for *flourishing* on both measures classified as *flourishing*, for *languishing* on both measures classified as *languishing*, and all others classified as *moderately mentally healthy*. Approximately 38.2% ( $n = 843$ ) of students met the criteria for *flourishing* mental health based on optimal cut scores, 39.4% ( $n = 869$ ) for *moderately mentally health*, and 22.5% ( $n = 497$ ) for *languishing* mental health.

To investigate if the selected cut scores on the BMSLSS and SEDS-S adequately classified students with *flourishing* and *languishing* mental health in the validation subsample, sensitivity, specificity, PPV and NPV were calculated for these cut scores on the validation subsample. Results are presented in Table 2. AUC values for the BMSLSS indicated good discriminatory value when identifying students who met diagnostic criteria for *flourishing* and *languishing* mental health, and sensitivity and specificity for both cut scores on the BMSLSS were within the acceptable range. Cross-validation of the SEDS-S cut scores with the validation subsample yielded AUC values indicative of fair discriminatory

value for identifying students who have *flourishing* and *languishing* mental health. Sensitivity and specificity estimates for both cut scores were within the borderline to acceptable ranges. Positive and NPVs for cut scores on both measures were similar to those found in the calibration subsample, with NPVs higher than PPVs.

**Analysis of variance.** To assess the validity and utility of the optimal cut scores selected on the BMSLSS and SEDS-S, differences among mental health groups on several outcomes were examined. Groups were created based on optimal cut scores on both the BMSLSS and SEDS-S, with students required to meet the cut score criteria on both measures in order to be classified as having *languishing* or *flourishing* mental health. An individual, for example, must score at least a 24 on the BMSLSS and no greater than a 20 on the SEDS to be classified as having *flourishing* mental health. To meet the languishing criteria, an individual must score no greater than a 21 on the BMSLSs and no lower than a 21 on the SEDS. Individuals who did not meet the cut score criteria on both measures were classified as having *moderate mental health*. Using the cut scores for measures of both SWB and distress, approximately 39% ( $n = 854$ ) of students met the criteria for *flourishing*, 21.4% ( $n = 469$ ) for *languishing*, and 39.6% ( $n = 866$ ) for *moderately mentally healthy*.

A series of one-way analysis of variance (ANOVA) was performed to examine group differences based on students' social-emotional and educational covariates. Mean scores for each group are presented in Table 3. Results indicate that there was a significant difference between groups on covitality, Welch ( $2, 1251.77$ ) = 492.69,  $p < .001$ , and Brown-Forsythe ( $2, 1947.73$ ) = 454.76,  $p < .001$ . Post-hoc comparisons indicated that students in the *flourishing* mental health group, on average, reported the highest levels of covitality, followed by students in the *moderately mentally healthy* group, and lastly the *languishing*

mental health group (see Table 3). The effect size was large,  $\eta^2 = .287$ . Differences in sense of school connectedness were also significant, Welch (2, 1183.33) = 235.48,  $p < .001$ , and Brown-Forsythe (2, 1654.10) = 230.00,  $p < .001$ . Effect size was large,  $\eta^2 = .18$ . Post-hoc tests indicated that all differences between groups were significant, with the *flourishing* group reporting the highest levels of school connectedness, followed by the *moderately mentally healthy* group, and finally the *languishing* group (see Table 3). Next, differences between groups on overall life satisfaction were examined based on responses to the one-item measure, and significant differences were found between groups, Welch (2, 995.84) = 477.41,  $p < .001$ , and Brown-Forsythe (2, 1054.38) = 469.03,  $p < .001$ . The effect size of this difference was large,  $\eta^2 = .346$ . On average, students in the *flourishing* group reported life satisfaction was 14 points higher than students in the *moderately mentally healthy* group and 41 points higher than students in the *languishing* mental health group. Differences between groups on depressed emotionality in the past 12 months were also significant, Welch (2, 1082.49) = 531.01,  $p < .001$ , and Brown-Forsythe (2, 1552.22) = 419.23,  $p < .001$ . The effect size was large,  $\eta^2 = .284$ . Differences on this measure were significant between all groups, with *flourishing* and *moderately mentally healthy* groups, on average, indicating that they have not felt sad or hopeless almost every day for two weeks in the past 12 months. Students in the *languishing* group, on average, indicated that they have felt this symptom of depressed emotionality in the past 12 months. Finally, differences across groups on self-reported course grades were examined, and test statistics indicated significant differences among groups, Welch (2, 1158.14) = 47.17,  $p < .001$ , and Brown-Forsythe (2, 1533.70) = 45.87,  $p < .001$ . Effect size was small,  $\eta^2 = .043$ . Although all differences were significant between groups, each group, on average, self-reported that they have mostly received B's. Overall, significant

differences on all measures between mental health groups were in the expected directions, with students in the *flourishing* group reporting significantly better outcomes than students meeting criteria for *moderately mentally healthy* and *languishing*.

## **Discussion**

The current study sought to identify optimal cut scores on brief measures of SWB and distress to be used for school-based dual-continua mental health screening with adolescents, with the intention of exploring a possible alternative approach to classification that is feasible for schools to carry out independently. Specifically, cut scores were selected based on students' positive mental health "diagnoses" according to Keyes' definition of SWB, which considers emotional, psychological, and social wellbeing when classifying an individual's positive mental health (Keyes, 2002). Optimal cut scores were identified to distinguish students with *flourishing* mental health and *languishing* mental health, as previous research suggests that these positive mental health "diagnoses" are meaningful for predicting critical outcomes in youth, including positive relationships, psychosocial functioning, and fewer instances of depression, conduct problems, and substance use (Keyes, 2006a, 2006b). To date, no studies on dual-continua mental health have investigated the optimal cut scores on measures of SWB and distress and the utility of these cut scores to make informed decisions about school-based prevention and intervention strategies following universal mental health screening.

Before carrying out ROC curve analyses, base rates of positive mental health diagnoses among the calibration subsample were examined. In the context of school-based screening, base rates are important to consider for several reasons (Kilgus & Eklund, 2016). Prior to screening, it is important to understand that base rates on an outcome of interest will

likely affect screening accuracy, with higher base rates leading to more false positive results (VanDerHeyden & Witt, 2005). Thus, higher base rates of students who are *languishing* would mean it is expected that more students will be identified as *languishing* by the screening measures than is indicated by the criterion measure (i.e., the MHC-SF). Second, base rates of *languishing* students should be compared with the percent of the student body a school can follow-up with given available resources in order to inform implementation of intervention strategies (Kilgus & Eklund, 2016). If the base rate of *languishing* students, for example, was higher than the proportion of students a school could feasibly follow-up with individually, then a school might decide to implement more class or schoolwide Tier 1 prevention strategies to mitigate social-emotional difficulties and promote positive youth development. Finally, base rates influence PPV and NPV, which are sample-based indices (Kilgus et al., 2018, Petscher, Kim, & Foorman, 2011). Therefore, if a small percent of students meet *languishing* criteria according to the MHC-SF, then PPV will likely be lower than NPV (Pescher et al., 2011).

Base rates for both subsamples indicated that more students met the criteria for *flourishing* (46% of the calibration subsample, 45.9% of the validation subsample) and *languishing* (15.2% of the calibration subsample, 15.6% of the calibration subsample) than in previous literature on positive mental health diagnoses among adolescents (Keyes, 2006a). Base rates in the present study for *flourishing* youth are encouraging given the significant differences in proximal outcomes across mental health classifications, all of which favored those classified as *flourishing*. It is possible that differences in base rates are an artifact of the samples studied, as Keyes' study looked at prevalence rates in a nationally-representative sample of adolescents (2006a) and the current study is based on item responses from five

schools in California. Alternatively, previous research examining the prevalence of positive mental health diagnoses with the MHC-SF might have underidentified youth experiencing social-emotional difficulties. The prevalence rates identified in the current study are more consistent with research suggesting that between 13-20% of youth experience a mental illness in a given year (Centers for Disease Control and Prevention, 2013). With a relatively small number of students meeting criteria for *languishing* mental health, PPV was much lower than NPV for the present study. Therefore, the rate of false positive cases classified as *languishing* by cut scores on the BMSLSS and SEDS-S was higher than optimal.

### **Cut Scores on Measures of SWB and Distress**

Optimal cut scores on the measures of SWB (i.e., BMSLSS) and distress (i.e., SEDS-S) were identified based on ROC curve analyses and previously stated criteria for sensitivity and specificity. Based on cut scores identified, individuals classified as *flourishing* by optimal cut scores on the BMSLSS and SEDS-S answered that they were, on average, “satisfied” with several aspects of their lives and found symptoms of distress to be only “somewhat true” of them. In contrast, individuals who were classified as *languishing* by optimal cut scores on the BMSLSS and SEDS-S answered that they were, on average, “somewhat satisfied” with different aspects of life. Still, symptoms of distress were, on average, “somewhat true” of students classified as *languishing* by optimal cut scores. This means that, on average, students classified as having both the highest and lowest levels of positive mental health experienced similar levels of distress. Ideally, cut scores for *flourishing* and *languishing* on the SEDS-S would quantitatively and qualitatively differ; however, in this study ROC analyses identified 20.5 and below to be the optimal cut score for *flourishing* and 20.5 and above to be the optimal cut score for *languishing*. As a result,

individuals with a total score of 20 on the SEDS-S were classified as *flourishing*, while individuals with a total score of just one point higher were classified as *languishing*. As the SEDS-S was not designed to be a measure of psychological disorders, but rather subsyndromal distress, it is possible that the SEDS-S does not adequately differentiate *languishing*, *flourishing*, or *moderate* mental health. The SEDS-S is a measure designed to assess symptoms of distress while still being palatable within a school setting for the first gate of mental health screening (e.g., asking “In the past month, it was hard for me to get excited about anything,” rather than, “My life is pointless”). Thus, students across positive mental health groups likely endorsed these symptoms to some degree, as some distress is normative. For schools that prefer to identify only their most at-risk students, a higher cut score on the SEDS-S or a measure of distress intended for more diagnostic purposes might be considered.

Results of ROC curve analyses with the calibration subsample suggest that the BMSLSS and SEDS-S have moderate diagnostic accuracy, with both measures doing a slightly better job of identifying individuals “diagnosed” with *languishing* mental health than *flourishing* mental health. This should not be considered a limitation of the measures, as the first priority of school-based wellness screening is to identify those most at risk for social emotional difficulties. Sensitivity and specificity estimates for selected cut scores on the BMSLSS were in the acceptable range ( $> .80$ ), suggesting that when the selected cut scores are applied to BMSLSS total scores, the measure does an acceptable job of correctly classifying individuals as *flourishing* and *languishing* (i.e., sensitivity) and correctly classifying individuals as not *flourishing* and not *languishing* (i.e., specificity). Sensitivity estimates for selected cut scores on the SEDS-S were approaching the acceptable range,



falling in the borderline range ( $> .70$ ). Specificity estimates for cut scores on the SEDS-S were lower than desired, falling in the borderline range ( $> .60$ ), indicating that the selected cut scores did not optimally classify individuals who are not *flourishing* and *languishing*. When applying practical implications to these results, we might conclude that utilizing selected cut scores on the SEDS-S will identify many more people as *flourishing* or *languishing* than is accurate (i.e., false positives). However, given the study's aims to prioritize sensitivity in the context of universal school-based screening, this is expected.

Positive and negative predictive values for selected cut scores indicated that the BMSLSS cut score for *flourishing* mental health (BMSLSS total score of 24 and above) had high PPV and NPV, suggesting that the BMSLSS correctly classified a high proportion of individuals as *flourishing* who also met criteria on the MHC-SF and correctly classified a high proportion of individuals who are not *flourishing* who do not meet the criteria for *flourishing* on the MHC-SF. This might be expected, as the BMSLSS and MHC-SF are both considered measures of SWB, and the BMSLSS total score was moderately correlated with each MHC-SF subscale mean score (see Table 1). When classifying individuals into the *languishing* mental health group, the selected cut score on the BMSLSS (total score of 20 and below) showed high NPV, with almost 96% of individuals who were identified as not *languishing* on the BMSLSS diagnosed similarly on the MHC-SF. However, less than half of students who were classified as *languishing* with this cut score actually met the diagnostic criteria for *languishing* on the MHC-SF, suggesting that over half of those identified for possible follow up services (i.e., the *languishing* group) by the BMSLSS might not be in need of more care (i.e., false positives). Given that base rates for *languishing* mental health were relatively low (15% in the calibration subsample), it was anticipated that PPV of

optimal cut scores to classify students as *languishing* would be lower on both measures than NPV. Considering the higher rates of false positives and prioritizing sensitivity over specificity within screening, practitioners who choose to employ the selected cut scores with students should also be equipped with the resources to do a second gate of screening with students classified as *languishing*, in which the first gate of screening is schoolwide and designed to catch all students in need of more care. In the second gate of screening, schools might select measures that prioritize specificity and high PPV to appropriately allocate Tier 2 and Tier 3 resources.

Similarly to ROC curve analyses with the BMSLSS, selected cut scores on the SEDS-S had higher PPV for identifying *flourishing* mental health than *languishing* mental health. While approximately 60% of individuals identified by the SEDS-S as *flourishing* also met criteria on the MHC-SF, approximately 26% classified as *languishing* by the SEDS-S met the diagnostic criteria for *languishing* on the MHC-SF. Therefore, the selected cut scores on the SEDS-S would likely over-identify students in need of immediate follow-up services. Selected cut scores on the SEDS-S had higher NPV, suggesting that the measure might do better in accurately identifying individuals who are not *flourishing* and not *languishing*. Overall, AUC values, sensitivity, and specificity estimates for the BMSLSS and SEDS-S indicated that these measures and selected cut scores may be acceptable for use in school-based wellness screening to classify individuals for follow-up assessment and care, with the understanding that these measures provide a brief assessment of students' mental health, and more specific screening instruments will likely be needed during follow-up.

The optimal cut scores identified on the BMSLSS and SEDS-S for classifying *flourishing* and *languishing* students also demonstrated acceptable sensitivity and acceptable

or borderline specificity with the validation subsample (see Table 2). Additionally, PPV and NPV for selected cut scores with the validation subsample were almost identical to PPV and NPV with the calibration subsample. These results suggest that findings with the calibration subsample replicated with a separate subsample and might not be simply an artifact of the sample characteristics. However, subsamples were created for the purposes of the current study, and replication among independent samples is needed to further validate this classification approach with the BMSLSS and SEDS-S.

### **Social-Emotional and Educational Covariates Across Mental Health Groups**

A series of one-way between-group ANOVAs allowed for examination of the validity and meaningfulness of the mental health groups formed based on selected cut scores on the BMSLSS and SEDS-S. Differences in outcomes previously demonstrated to be indicative of youths' wellbeing and positive mental health were investigated across mental health groups. ANOVA and post-hoc comparisons indicated that all three mental health groups significantly differed on all outcomes, including social-emotional strengths, school connectedness, overall life satisfaction, depressed emotionality, and self-reported grades (see Table 3). Students classified into the *languishing* group according to selected cut scores on the BMSLSS and SEDS-S reported, on average, that statements about strengths were "somewhat true" of them, while students classified as *flourishing* and *moderately mentally healthy* reported statements about strengths to be "pretty much true" of them. Furthermore, individuals classified as *flourishing* reported, on average, that they felt connected to their school, while students classified as *moderately mentally healthy* and *languishing* reported that they neither felt connected nor didn't feel connected to school. This is consistent with previous research which found students with high levels of SWB and low levels of distress (i.e., flourishing or

thriving) reported the highest levels of school belonging compared to their peers (Moffa et al., 2016). Considering the large percent of students who reported, on average, that they neither feel connected nor disconnected from school, a school with similar results might implement a schoolwide intervention to promote school belonging, rather than address these outcomes at the Tier 2 and Tier 3 level with individuals.

Large significant differences were found between mental health groups based on students' overall life satisfaction, with students classified as *languishing* reporting life satisfaction levels over 40 points lower, on average, than students classified as *flourishing* and over 25 points lower, on average, than students classified as *moderately mentally healthy*. These results suggest that classification criteria identified by ROC curve analyses were useful in identifying differences in overall appraisal of life satisfaction, which is consistently demonstrated to be strongly correlated to other positive youth outcomes (Proctor, Linley, & Maltby, 2009). Moreover, significant differences were found across groups based on the occurrence of depressed emotionality in the past 12 months, with students classified as *languishing* reporting, on average, that they have felt so sad or hopeless every day for a two week period that their functioning was impaired. Students classified as *flourishing* and *moderately mentally healthy* did not endorse this item, on average.

Differences on depressed emotionality across groups further demonstrate the importance of asking all students about their mental health and following up with more specific screening and care. If a school was responding to results like these, they might implement more intensive Tier 2 services for students identified as *languishing* by cut score criteria. Finally, although differences in self-reported grades were significant across groups, they may not be interpreted as meaningful for differentiating between groups, as all groups reported earning

mostly B's, on average. However, practically this implies that students' wellbeing cannot be assessed based solely on their self-reported academic performance, and youths' wellbeing is influenced by much more than students' course grades.

The presence of both SWB and the absence of distress appeared to play significant roles in other important mental health outcomes among youth, as students who were classified as *flourishing* on both the BMSLSS and SEDS-S also reported more positive outcomes, on average. Overall, these results suggest there is meaningful validity to the cut scores selected by ROC curve analyses, and that SWB is more complex than simply "high" and "low." However, more research is needed to better understand the continuum of distress, as selected cut scores on the SEDS-S suggested distress on a screening measure can be differentiated by "normative" and "high." Still, differences in covariates across groups demonstrated that meeting the criteria for *moderately mentally healthy* or *flourishing* on at least one measure of mental health is related to improved outcomes compared to individuals classified as *languishing* on both measures, providing further evidence for the utility of dual-continua mental health screening.

### **Implications for Practice and Scholarship**

The present study offers a feasible classification approach following school-based DCM screening by identifying optimal cut scores on two measures of SWB and distress. School practitioners seeking to implement prevention and early intervention efforts through universal mental health screening could administer the BMSLSS and SEDS-S to all students and apply cut scores identified in this study to help classify students and appropriately assign resources. Students with total scores of 24 or above on the BMSLSS and 20 or below on the SEDS-S would be classified as having *flourishing* mental health. Practitioners could assume

with some degree of certainty that students in this group are experiencing outcomes associated with positive youth development, but they can still benefit from Tier 1 prevention efforts. Students scoring 20 or below on the BMSLSS and 21 or above on the SEDS-S would be classified as *languishing*, with a second gate of screening likely warranted based on the high rate of false positive cases in identifying this group. Still, outcomes for this group on life satisfaction, depressed emotionality, and school connectedness warrant follow-up with targeted and intensive intervention efforts. Finally, students would be classified as *moderately mentally healthy* in several situations: (1) scoring a 21, 22, or 23 on the BMSLSS and any score on the SEDS-S, (2) scoring a 24 or above on the BMSLSS but a 21 or above on the SEDS-S, or (3) scoring a 20 or below on the BMSLSS but a 20 or below on the SEDS-S. Based on outcomes of interest in the current study, these are students that can also benefit from Tier 1 prevention and intervention efforts. Additionally, practitioners might consider individual follow up with students who were classified as *moderately mentally healthy* but met criteria for *languishing* based on their SEDS-S total scores, as these students might be experiencing heightened distress that necessitates targeted follow-up strategies. While the current study offers one approach to classification with cut scores on two measures of DCM, practitioners and researchers hoping to classify students based on other measures of DCM will need to identify new cut scores based on diagnoses of positive mental health.

The findings from the current study have several implications for scholars and practitioners implementing a DCM framework when conceptualizing youths' mental health and wellness. The selected cut scores on measures of SWB and distress classified students into meaningful mental health groups, as evidenced by the significant differences across groups in important outcomes of positive youth development. Not only were outcomes

significantly and meaningfully different between those classified as *flourishing* and *languishing*, but there were significant differences between those classified as *moderately mentally healthy* and *languishing*, as well as *moderately mentally healthy* and *flourishing*. These results add to the continually strong evidence that the DCM is important when assessing the social-emotional needs of adolescents, as more desirable scores (i.e., those that are classified as *flourishing* or *moderately mentally healthy*) on either a measure of SWB or distress may help buffer against more severe negative outcomes. Moreover, significant differences in outcomes between those classified as *moderately mentally healthy* and *flourishing* suggest there is value in having both high levels of SWB and lower, or normative, levels of distress.

### **Limitations and Future Directions**

The current study had several limitations which future research should address. While the measures used to evaluate DCM mental health were selected based on empirical research and brevity within the screening context, other measures can be utilized to assess dual-continua mental health. For example, selection of the BMSLSS to assess adolescents' SWB was based on previous DCM research with youths. However, some studies have used both the BMSLSS and PANAS-C (Laurent et al., 1999) to measure SWB, defining the construct as overall appraisal of life satisfaction *and* affective wellbeing. Future research might explore an optimal cut score on the PANAS-C, as well, so that students are classified based on cut scores on the BMSLSS, PANAS-C, and SEDS-S. Future research might also investigate this classification approach with the SEHS-S to measure SWB and the SEDS-S to measure distress, which was developed to be co-administered with the SEHS-S in a school-based screening context. The SEDS-S has demonstrated good construct validity and the

*Internalizing Distress* factor is strongly correlated to other measures of distress, including the *Patient Health Questionnaire* (Kroenke, Spitzer, & Williams, 2001) and the *Generalized Anxiety Disorder Scale* (Spitzer, Kroenke, Williams, & Löwe, 2006). Still, the SEDS-S is not a measure of clinical distress, and might benefit from further validation to better differentiate students most in need of follow-up care. With any measures practitioners choose, optimal cut scores will need to be investigated prior to classifying students into mental health groups.

A diagnostic criterion measure was chosen based on the ultimate goal to help students be well. In the absence of a gold standard for positive mental health diagnoses, the MHC-SF was chosen as the criterion measure for ROC curve analyses. More research is needed to examine this measure with adolescents to better understand prevalence of positive mental health diagnoses among this population, as well as validity of these diagnoses with other outcomes of positive mental health. It is important to note that optimal cut scores on the BMSLSS and SEDS-S identified in the present study are based on diagnostic criteria according to the MHC-SF, and cut scores may change with a different criterion measure. Future directions of research might consider identifying optimal cut off scores on measures of SWB and distress based on different criterion measures, such as those utilized to assess clinical levels of distress or academic achievement.

While criteria chosen for selection of cut scores on the BMSLSS and SEDS-S were based on empirical recommendations for a first gate of universal mental health screening, future research might consider prioritizing specificity over sensitivity based on individual schools' goals for screening and available resources for multitiered systems of support. Additionally, more research is needed to examine the validity of selected cut scores with population-based samples of students to understand how these cut scores differentiate across



cultural groups, gender, and grade. Future research should also investigate longitudinal outcomes associated with this cut score approach to classification to better understand if this approach adds to predicting positive youth outcomes later in life.

The present study offers a preliminary investigation into one alternative approach to classification based on high school students' responses to brief measures of SWB and distress. Although initial findings indicate that cut scores identified on these measures allow for meaningful classification of students based on DCM, more research is needed to understand how to best assess and classify students. While this approach is feasible for practitioners and researchers, it still requires cut scores to be imposed, which will always lead to some misidentification. It is possible that empirically-based classification approaches, like Latent Profile Analysis (LPA), can be implemented to more accurately classify students based on observed item response patterns. Rather than group individuals based on sample-specific or criterion-referenced cut scores, LPA has the potential to classify students into emergent groups based on observed item responses that are measuring an underlying latent construct (e.g., DCM mental health). Overall, research on school-based DCM screening should continue to focus on finding accurate approaches to classification that increase schools' abilities to successfully and independently implement universal DCM screening, and in turn increase schools' abilities to help every student be well.

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Table 1

*Variable Descriptive Statistics and Correlations Among Study Variables*

Variable								Range	<i>M</i>	<i>SD</i>
<b>Calibration Subsample</b>	1	2	3	4	5					
1. BMSLSS Total Score	-							6-30	22.42	5.22
2. SEDS-S Total Score	-.51	-						10-40	20.85	8.42
3. MHC-SF, Emotional Wellbeing	.67	-.51	-					0-5	3.42	1.40
4. MHC-SF, Psychological Wellbeing	.66	-.45	.86	-				0-5	3.22	1.43
5. MHC-SF, Social Wellbeing	.62	-.41	.76	.82	-			0-5	2.66	1.52
<b>Validation Subsample</b>	1	2	3	4	5	6	7	Range	<i>M</i>	<i>SD</i>
1. BMSLSS Total Score	-							6-30	22.55	5.15
2. SEDS-S Total Score	-.47	-						10-40	20.74	8.46
3. SEHS Mean Score	.66	-.32	-					1-4	2.88	0.52
4. SCS Mean Score	.48	-.31	.51	-				1-5	3.52	0.81
5. Overall Life Satisfaction	.63	-.46	.55	.36	-			0-100	76.90	26.05
6. Depressed Emotionality	-.42	.58	-.33	-.27	-.40	-		1-2	1.35	0.48
7. GPA	-.26	.01	-.29	-.26	-.22	.14	-	1-8	2.92	1.63

*Note.* BMSLSS = Brief Multidimensional Student Life Satisfaction Scale. SEDS-S = Social Emotional Distress Survey – Secondary. MHC-SF = Mental Health Continuum – Short Form. SEHS-S = Social Emotional Health Survey – Secondary. SCS = School Connectedness Scale. GPA = Grade Point Average. All correlations are significant,  $p < .01$ .

Table 2

*Diagnostic Accuracy Statistics Associated with Subjective Wellbeing and Distress Cut Scores*

Scale	AUC [95% CI]	Cut score	SE	SP	PPV	NPV
<b>Calibration Subsample</b>						
<i>BMSLSS</i>						
Flourishing	.852 [.837-.868]	<b>23.5</b>	<b>.803</b>	<b>.760</b>	<b>.739</b>	<b>.819</b>
		22.5	.863	.674	.692	.853
Languishing	.875 [.855-.894]	19.5	.750	.840	.457	.949
		<b>20.5</b>	<b>.804</b>	<b>.783</b>	<b>.40</b>	<b>.957</b>
		21.5	.863	.727	.362	.967
		22.5	.905	.658	.322	.975
<i>SEDS-S</i>						
Flourishing	.752 [.732-.773]	<b>20.5</b>	<b>.759</b>	<b>.618</b>	<b>.603</b>	<b>.752</b>
Languishing	.766 [.738-.793]	<b>20.5</b>	<b>.765</b>	<b>.613</b>	<b>.262</b>	<b>.936</b>
<b>Validation Subsample</b>						
<i>BMSLSS</i>						
Flourishing	.828 [.810-.845]	23.5	.795	.715	.704	.803
Languishing	.850 [.827-.872]	20.5	.746	.791	.398	.944
<i>SEDS-S</i>						
Flourishing	.742 [.721-.762]	20.5	.767	.610	.626	.754
Languishing	.745 [.716-.774]	20.5	.740	.620	.265	.928

*Note.* AUC = area under the curve; SE = sensitivity; SP = specificity; PPV = positive predictive value; NPV = negative predictive value; 95% CI = 95% confidence interval. Bolded cut scores indicate optimal cut scores chosen for validity with the validation subsample.

Table 3

*Mean Scores on Outcome Variables for Positive Mental Health Groups*

<b>Group</b>	<b><i>n</i></b>	<b>%</b>	<b>SEHS-S</b> <i>M (SD)</i>	<b>SCS</b> <i>M (SD)</i>	<b>Life Satisfactio</b> <b>n</b>	<b>Depressed Emotion</b> <i>M (SD)</i>	<b>GPA</b> <i>M (SD)</i>
<b>Flourishing</b>	854	39.0%	<i>Pretty much true</i> 3.18 (0.42)	<i>Agree</i> 3.89 (0.67)	91.28	<i>No</i> 1.08 (0.27)	<i>Mostly B's</i> 2.55 (1.43)
<b>Moderately Mentally Healthy</b>	866	39.6%	<i>Pretty much true</i> 2.81 (0.47)	<i>Neither disagree nor agree</i> 3.45 (0.75)	76.93	<i>No</i> 1.41 (0.49)	<i>Mostly B's</i> 3.00 (1.62)
<b>Languishing</b>	469	21.4%	<i>Somewhat true</i> 2.45 (0.41)	<i>Neither disagree nor agree</i> 2.99 (0.79)	49.97	<i>Yes</i> 1.75 (0.43)	<i>Mostly B's</i> 3.44 (1.82)

*Note.* SEHS-S = Social Emotional Health Survey – Secondary (range 1-4). SCS = School Connectedness Scale (range 1-5). Life Satisfaction (range 0-100). GPA = Grade Point Average (range 1-8). All means are significantly different between groups,  $p < .001$ .

**Study 2: Exploring the Use of Latent Profile Analysis to Classify High School Students'**

**Dual-Continua Mental Health**



## **Abstract**

The dual-continua model of mental health, in which wellbeing and distress are considered separate continua encompassing individuals' mental health, has previously been explored among several samples of adolescents. However, across these studies no consensus on methodology or criteria to classify students into groups based on the dual-continua model has emerged. The current study employed latent profile analysis to explore empirically-based latent classes of dual-continua mental health among a sample of high school students from five high schools in California. Students ( $N = 4,677$ ) reported on their subjective wellbeing and distress as part of survey administration in the fall of 2017. Additionally, students responded to questions related to social-emotional and educational covariates, and substance use. Latent profile analyses did not indicate a best fitting model that could be replicated or reliably used to further recommendations for school practitioners. Implications are discussed.

*Keywords:* dual-continua model, latent profile analysis, adolescents

## **Exploring Latent Profiles of Dual-Continua Mental Health among High School Students**

The World Health Organization (WHO) has defined health as “a state of complete physical, mental, and social wellbeing and not merely the absence of disease or infirmity” (WHO, 1964, p. 1). Consistent with this definition, contemporary research on youths’ mental health has begun to promote the dual-continua model (DCM; also known as the dual-factor model) of mental health, which defines mental health as not only the absence of psychological distress, but also the presence of indicators of enhanced youth development and wellbeing (Greenspoon & Saklofske, 2001). Thus, social-emotional wellbeing and distress are conceptualized as separate constructs, both of which are part of developing a comprehensive picture of youths’ mental health. Previous literature on the DCM has assessed individuals’ mental health by obtaining information on one’s feelings about their subjective wellbeing (SWB) and distress, with SWB defined as “the way in which and the reasons why individuals experience their lives positively” (Antaramian, Huebner, Hills, & Valois, 2010, p. 462). SWB has previously been assessed by measuring individuals’ self-reported life satisfaction (Greenspoon & Saklofske, 2001), with some literature also including measures of positive and negative affect (e.g., Antaramian et al., 2010; Suldo, Thalji-Raitano, Kiefer, & Ferron, 2016). Previous literature on the DCM among youth has rationally formed four mental health groups based on researcher-generated binary SWB or positive mental health and distress groups. This has contributed to inconsistencies in the way students have been classified, with methodology varying across studies and samples. To explore an alternative DCM method to classify students based on SWB and distress, the current study examined the use of an empirical approach to define mental health groups among adolescents.

When applied in the school-based, universal screening context, a DCM approach to the conceptualization and assessment of youths' mental health provides a strategy with which to prevent and treat distress while also fostering the positive youth development of all students. In contrast to deficit-focused mental health screening, which asks students about feelings of distress and involvement in at-risk behaviors, DCM research provides evidence that important information can be gleaned when screening includes indicators of both SWB and distress. In addition to the typically identified groups in deficit-based mental health screening (i.e., "normative" and "at-risk"), school-based screening that follows a DCM approach has previously highlighted two additional groups of students that are not typically identified when only asking about distress: (a) a group that reports low levels of SWB and distress, and (b) a group that reports high levels of SWB and distress. Previous research employing a DCM of mental health has demonstrated value in treating SWB and distress as separate, yet related constructs. Greenspoon and Saklofske (2001), for instance, found that students ( $N = 407$ ; Grades 3-6) who reported low SWB and low distress (i.e., *dissatisfied*) did not report significantly different scores in interpersonal relations and scholastic competence than those students who reported low SWB and high distress (*distressed*). Additionally, students who reported high SWB and high distress (*externally maladjusted*) did not report significantly different scores in global self-worth and sociability than those who reported high SWB and low distress (*well-adjusted*). If only psychopathology had been assessed, difficulties with interpersonal relationships for youth in the *dissatisfied* group and existing strengths for youth in the *externally maladjusted* group would not have been identified, leading school teams to make incomplete conclusions about the status of students' mental

health. These results highlight the value of asking youth about SWB and symptoms of distress.

Since Greenspoon and Saklofske's (2001) examination of DCM groups among youth, several studies have found significant differences in outcomes of youth depending on level of both SWB and distress. Suldo and Shaffer (2008) found significant differences on several outcomes based on middle school students' ( $N = 349$ ) levels of SWB, including family and peer support, perceptions of academic abilities, self-regulation, and number of absences. Those that reported higher levels of SWB, despite their self-reported levels of psychopathology, were more likely to endorse more social support and self-regulation, higher perceptions of their academic abilities, and fewer absences. Likewise, Antaramian and colleagues (2010) examined the differences across DCM groups in school engagement and academic achievement for seventh- and eighth-grade students ( $N = 920$ ). Findings indicated that higher SWB significantly predicted more student engagement and family support and higher grade point averages (GPA). In a follow-up to Antaramian and colleagues' (2010) study five months later, Lyons, Huebner, Hills, and Shinkareva (2012) found that SWB reported at Time 1 was a significant predictor of emotional, cognitive, and behavioral engagement and GPA five months later, above and beyond distress. This suggests that distress is not the only factor in understanding important social emotional and academic outcomes for youth.

### **Existing Classification Methods for the DCM among Youth**

Currently, there is no agreed upon strategy for classifying students into DCM mental health groups based on their SWB and distress. In each of the research studies described above, criteria to create DCM groups were based on a research-selected cut score or

distribution of scores on a normative curve. Most research on the DCM has classified students into groups based on norms (e.g.,  $T$  score  $> 60$ ,  $z$  score  $> 1.00$ ), using published norms when available and local, sample-specific norms for other constructs (Antaramian et al., 2010; Kelly et al., 2012; Suldo & Shaffer, 2008). For example, consistent with Suldo and Shaffer (2008), Suldo and colleagues (2016) classified 500 middle school students into four DCM groups based on scores on the *Students' Life Satisfaction Scale* (SLSS; Huebner, 1991), the *Positive and Negative Affect Scale for Children* (PANAS-C; Laurent et al., 1999), the internalizing composite of the *Behavior Assessment System for Children, Second Edition Self-Report of Personality* form (BASC-2 SRP; Reynolds & Kamphaus, 2004), and the externalizing composite of the *BASC-2 Teacher Rating Scale* (TRS; Reynolds & Kamphaus, 2004). Students' levels of distress were based on  $T$  scores, in which  $T$  scores of 60 or above on the BASC-2 SRP or BASC-2 TRS indicated a high level of psychopathology (Suldo et al., 2016). Since no published norms for SWB currently exist in the literature, cut scores for students' scores on the SLSS and PANAS were based on the proportions of students classified as high and low psychopathology. Thus, all students above the 30<sup>th</sup> percentile in SWB based on  $z$ -scores were classified as reporting average to high SWB, while students below the 30<sup>th</sup> percentile were classified as reporting low SWB (Suldo & Shaffer, 2008; Suldo et al., 2016). The four resulting groups were termed *complete mental health*, *vulnerable*, *symptomatic but content*, and *troubled*.

While classification based on published norms can facilitate comparison of youths' mental health across samples, published norms have not been established for measures of SWB employed in studies of the DCM approach (Suldo & Shaffer, 2008). Classification based on sample-specific norms inhibits school psychologists from comparing results of

school-based universal mental health screening longitudinally and across samples. A closer examination of classification methods using sample-specific norms reveals the differences in mean scores of SWB across samples. For example, the cut score used for SWB by Suldo and Shaffer (2008) was 4.10 and above, by Antaramian et al. (2010) it was 3.39 and above, by Suldo et al. (2016) it was 4.0 and above, and by Kelly et al. (2012) it was 3.45 and above at Time 1 and 3.78 and above at Time 2. As a consequence, individuals who were classified as having *complete mental health* in some studies would fall into the *vulnerable* group in other studies with higher cut score criteria, which makes comparisons of groups across samples questionable. Furthermore, the use of published and sample-specific norms to classify students into DCM groups leads to other problems, particularly when following students across time. Reliance on a normative curve to determine cut score criteria results in similar proportions of students in each group across time, even if students report improving or worsening SWB and distress. In Kelly and colleagues' study (2012), for example, similar proportions of students fell into each DCM group at Time 1 and 2, despite mean life satisfaction scores decreasing from Time 1 to Time 2. Regardless if the overall health of the student body is improving, there will be similar numbers of students in groups within a school. Therefore, school teams might experience challenges in interpreting longitudinal trends in students' mental health, as differences will be masked because of the classification approach used. Thus, practitioners could allocate resources ineffectively.

### **A Proposed Alternative: Latent Profile Analysis**

Latent Profile Analysis (LPA), or Latent Class Cluster Analysis (LCCA), is a type of mixture modeling that offers an empirical alternative to cut scores (Nylund, Bellmore, Nishina, & Graham, 2007; Masyn, 2013). While classifying individuals using cut scores

relies on logical decision-making about appropriate cut score values, LPA allows for the classification of people based on underlying empirically identified latent classes, or homogenous groups, with similar patterns of responses to indicators within classes (Masyn, 2013). According to Nylund and colleagues (2007), grouping people by cut scores may create groups that are not homogenous within groups on covariates and outcomes of interest and do not meaningfully differentiate between groups on the same covariates and outcomes. In contrast, LPA is based on observed data and assumes that class membership represents a latent construct (Nylund et al., 2007). The use of LPA within a school setting allows for decisions to be made based on within-class homogeneity and between-class differentiation, which facilitates decisions based on youths' mental health and wellbeing in a school-based universal screening context (Masyn, 2013).

Previous literature suggests that the use of cut scores when measuring students' SWB and distress is common practice; however, research has begun to examine underlying mental health profiles using the DCM approach to mental health. In a study of high school students across California ( $N = 12,279$ ), Rebelez-Ernst (2015) conducted a three-phase mixture model using Latent Class Analysis (LCA) with covariates to investigate profiles of mental health among students based on multiple indicators of positive mental health (termed *covitality*) and internalizing and externalizing indicators of distress. In the first two phases of the study, an unconditional LPA and LCA were conducted to specify the underlying latent structure of positive mental health profiles and distress classes, respectively. The resulting LPA and LCA models with the best fit were then cross-tabulated to better understand students' mental health from a DCM perspective. Additionally, post-hoc mean difference tests were carried out to gauge a more comprehensive picture of each mental health profile through measures of

risk and quality of life. After cross-tabulating positive mental health profiles and distress classes, results indicated that there were 16 unique groups of students, with each group representing a unique mental health profile. Most students (66% of females and 71% of males) were classified into the group with above average positive mental health and no psychosocial distress. Meaningful differences between classes existed in school connectedness, meaningful participation in school, and self-reported grades.

In an additional application of the DCM using LCA with South Korean adolescents, Kim, Dowdy, Furlong, and You (2016) specified latent classes for positive mental health and distress separately, then cross-tabulated the optimal number of positive mental health classes with the optimal number of distress classes. Five positive mental health and three distress profiles were selected as the final models and then cross-tabulated, resulting in 15 latent DCM mental health classes. The proportion of students in each DCM class ranged from less than 1.0% (*high strengths with at-risk internalizing and externalizing distress*) to 27% (*average strengths with no distress*), suggesting that some classes may not have been substantively meaningful.

Alternatively, Moore (2017) utilized a series of LPA models to empirically investigate subtypes of DCM mental health among high school students ( $N = 332$ ) by simultaneously examining indicators of positive mental health and distress, rather than cross-tabulating separate profiles of positive mental health and distress. Moore (2017) suggested that examining strengths and distress within the same unconditional model is more parsimonious and decreases the likelihood that individuals are incorrectly classified into both positive mental health and distress profiles. Results of cross-sectional LPA models for three years of data supported a four-class solution in Grades 9, 10, and 11: (a) *complete mental*



*health* (highest means on indicators of positive mental health, lowest means on indicators of distress), (b) *moderately mentally healthy* (high-average means on positive mental health, low means on distress), (c) *symptomatic but content* (high-average means on positive mental health, higher means on distress), and (d) *troubled* (below-average means on positive mental health, average to above-average means on distress). Findings from Moore's (2017) study suggest that although empirically-based groups of DCM mental health among high school students were similar to groups obtained from cut scores, there were also noteworthy differences, including the emergence of a *moderately mentally healthy* class. This group was not present in previous DCM research but represented the largest proportion of students in that study (43.4% in Grade 9, 32.0% in Grade 10, 44.3% in Grade 11). Additionally, the previously identified *vulnerable* group did not emerge in the optimal LPA model.

There are notable limitations to previous literature exploring DCM health classes among adolescents that future research should address. Previous studies examined DCM classes specific to relatively small samples of adolescents (i.e.,  $N = 1,190$  for Kim et al., 2016;  $N = 332$  for Moore, 2017), and therefore results might not be generalizable beyond the school(s) of interest. Additionally, the optimal number of classes identified varied between studies. Kim and colleagues (2016) and Rebelez-Ernst (2015) cross-tabulated classes of positive mental health with classes of distress and identified 15 and 16 profiles of mental health, respectively. Moore (2017) identified four classes of complete mental health when conducted the more parsimonious approach of simultaneously specifying indicators of positive mental health and distress. As current research is limited in the application of LCA to DCM mental health screening, further research is needed to investigate the validity and generalizability of these empirically-based DCM classes on other samples of students. By

examining DCM mental health classes among a large, diverse sample of students, there is potential for schools to apply these classes to results of future mental health screening and make informed decisions about prevention and intervention strategies. Provided future studies demonstrate replication and generalizability of findings, there is potential for these latent classes to inform empirically-based cut scores for classification in the context of school-based mental health screening.

### **Predictors and Outcomes of Adolescents' Mental Health**

As the classification approaches continue to improve for DCM approaches, including the use of LPA, there is still a need to further understand predictors and outcomes of students based on mental health group or class. The direction and strength of demographic traits as predictors of DCM group membership are not yet well understood, as previous research has demonstrated inconsistent results regarding the role of demographic variables in predicting youths' mental health (Merikangas, Nakamura, & Kessler, 2009). While several studies examining the DCM among adolescents have investigated associated outcomes of group membership, more research is needed to gain a comprehensive understanding of students' experiences within each group.

### **Demographic Predictors of Adolescent Students' Mental Health**

The relation between demographic variables and adolescents' DCM group membership has varied in previous research studies. In regards to gender, previous literature has found adolescent females to experience a higher prevalence of depression and anxiety, while adolescent males are reported to experience a higher prevalence rate of attention deficit-hyperactivity disorder (ADHD) and conduct disorder (Merikangas et al., 2009). When examining the impact of gender in predicting SWB and pathology or distress among

adolescents, Suldo and Shaffer (2008) found that the resulting proportions of girls and boys in each mental health group were representative of the total sample. However, a more recent comparison found high school girls to be overrepresented in the *troubled* group (low SWB and high psychopathology; Suldo et al., 2016). Moore's (2017) examination of latent profiles of DCM mental health resulted in girls more likely to fall into the *symptomatic but content* group (high covitality and high distress) than the *complete mental health* group (high covitality and low distress) in Grades 9 and 10, but no significant gender effects were present in Grade 11.

The effects of ethnicity/race and economic background on adolescent mental health have also been inconsistent, which may be due to small sample sizes of adolescents from ethnic and racial minority backgrounds and low-income communities (Merikangas et al., 2009). While Suldo and colleagues (2016) found no significant differences in DCM membership based on ethnicity among high school students, Moore (2017) found that ethnicity and race were significantly associated with mental health group membership. Results of Moore's (2017) study indicated that Latinx students were more likely to report high levels of distress compared to non-Latinx peers, although it is possible findings were at least partially due to the disproportionately large number of Latinx students in the sample. Additionally, previous studies examining the DCM among adolescents have identified group differences based on economic background, with students from high economic backgrounds overrepresented in the *complete mental health* group and students with low economic backgrounds underrepresented in this group (Suldo & Shaffer, 2008; Suldo et al., 2016). In the same studies, the *troubled* group included a higher proportion of students from low economic backgrounds and a lower proportion of students from high economic backgrounds

compared to the total samples. More research is needed to better understand how latent profiles of adolescents' mental health relate to adolescents' ethnicity, gender, and economic background.

### **Covariates of Adolescents' Mental Health**

The relations between adolescents' mental health and other important indicators of positive youth development have been examined in several studies of the DCM with adolescents. High school students in the *complete mental health* and *moderately mentally healthy* latent classes have reported higher life satisfaction (Moore, 2017), school connectedness (Rebelez-Ernst, 2015), and academic achievement (Moore, 2017; Rebelez-Ernst, 2015). Additionally, high school students in the *symptomatic but content* and *troubled* groups have reported more frequent symptoms of depression and anxiety (Moore, 2017). The relation between DCM mental health and substance use is inconsistent. Rebelez-Ernst (2015) found that there were some significant differences in risk behaviors between DCM classes, including tobacco, alcohol, marijuana, pain pills, and drinking and driving, but there were fewer significant differences across groups for males than females.

### **The Current Study**

In three studies that examined underlying latent classes of DCM mental health among adolescents, differences were apparent in the number of optimal classes identified based on different methodological approaches to LPA, characteristics of the samples used, and strength of demographic variables in predicting group membership (Kim et al., 2016; Moore, 2017; Rebelez-Ernst, 2015). Therefore, previous findings might not generalize to a wide range of students when used for mental health screening. The current study utilized LPA to investigate DCM subtypes among a sample of high school students based on self-reported

SWB and distress. Following Moore (2017), indicators of SWB and distress were specified in the model simultaneously to optimize parsimony and increase validity of emerging latent classes. It was hypothesized that results of the current study would enhance school teams' abilities to identify students' class membership following administration of DCM mental health measures. Furthermore, demographic covariates of high school students' mental health, including gender, ethnicity, and economic background, were investigated to examine their relation to DCM profiles and outcome variables. Proximal distals of interest were based on previous findings suggesting significant relations between adolescents' DCM mental health and social-emotional strengths, depressed emotionality, school connectedness, self-reported grades, and substance use. Specifically, the current study aimed to answer the following research questions:

RQ1: What is the underlying number of latent DCM mental health profiles based on indicators of SWB and distress for high school students? Do these classes replicate with a separate subsample of participants?

RQ2: What is the relation between the underlying latent DCM mental health profiles and self-reported cultural group, gender, and economic circumstances?

RQ3: How do the underlying DCM mental health profiles relate to students' self-reported social-emotional strengths, depressed emotionality, school connectedness, self-reported grades, and substance use?

## **Method**

### **Participants**

Participants were a cross-sectional sample of high school students (Grades 9 through 12) from randomly chosen public schools in California. The first five high schools to

participate in a large statewide survey were included in analyses for the current study ( $N = 4,677$ ). A randomized split-half sample design was employed, in which analyses were performed on one subsample (i.e., the calibration subsample) and validated on the other half of the sample (i.e., the validation subsample).

**Calibration subsample.** The calibration subsample consisted of approximately 24.6% ( $n = 573$ ) ninth grade students, 24.4% ( $n = 565$ ) tenth grade students, 29.0% ( $n = 674$ ) eleventh grade students, 21.9% ( $n = 508$ ) twelfth grade students, and 0.2% ( $n = 5$ ) did not indicate grade or marked “other.” Approximately 51% of students identified as female, 48.1% as male, and 0.9% chose not to identify. Students’ self-reported race were as follows: 38.1% ( $n = 885$ ) White, 35.9% ( $n = 834$ ) mixed races, 10.9% ( $n = 254$ ) Asian, 4.0% ( $n = 92$ ) American Indian or Alaska Native, 2.8% ( $n = 64$ ) Black or African American, 1.3% ( $n = 30$ ) Native Hawaiian or Pacific Islander, and 7.1% ( $n = 166$ ) who chose not to identify. Approximately 45.6% ( $n = 1,061$ ) of participants identified as Hispanic or Latino origin. Students were also asked if they receive free and reduced-price lunches at school, with 39.2% ( $n = 911$ ) reporting “yes” and 8.4% ( $n = 195$ ) reporting that they did not know.

**Validation subsample.** The validation subsample included 25.6% ( $n = 602$ ) ninth grade students, 23.6% ( $n = 556$ ) tenth grade students, 29.1% ( $n = 685$ ) eleventh grade students, 21.3% ( $n = 495$ ) twelfth grade students, and 0.4% ( $n = 10$ ) did not indicate grade or marked “other.” Approximately 52.5% of students identified as female, 47.1% as male, and 0.4% chose not to identify. Students’ self-reported race were as follows: 38.3% ( $n = 901$ ) White, 37.5% ( $n = 883$ ) mixed races, 10.2% ( $n = 241$ ) Asian, 3.2% ( $n = 76$ ) American Indian or Alaska Native, 2.6% ( $n = 56$ ) Black or African American, 1.6% ( $n = 37$ ) Native Hawaiian or Pacific Islander, and 6.7% ( $n = 158$ ) who chose not to identify. Forty five percent ( $n =$

1,059) of participants identified as of Hispanic or Latino origin. When asked if students were currently receiving free or reduced lunches at school, 38.3% ( $n = 901$ ) reported “yes” and 8.7% ( $n = 204$ ) reported that they did not know.

### **Dual-Continua Model Mental Health Measures**

**SWB.** A mean score on the *Brief Multidimensional Student’s Life Satisfaction Scale* (BMSLSS; Seligson, Huebner, & Valois, 2003) was used to measure students’ SWB. The measure has previously been used in DCM research as an indicator of SWB (Greenspoon & Saklofske, 2001; Moffa et al., 2016; Ng, Huebner, Maydeu-Olivares, & Hills, 2017). The BMSLSS is a five-item self-report measure of students’ satisfaction with five domains, each represented by one item (i.e., “I would describe my satisfaction with my family life/friendships/school experience/myself/where I live as...”). Confirmatory factor analysis has supported a one-factor structure with strong loadings (.53 - .79) and adequate fit (Ng et al., 2017). Longitudinal measurement invariance was supported for a sample of adolescents across a one-year period (Ng et al., 2017). Students responded to the measure using a six-point scale (1 = *very dissatisfied*, 2 = *dissatisfied*, 3 = *somewhat dissatisfied*, 4 = *somewhat satisfied*, 5 = *satisfied*, and 6 = *very satisfied*), with higher scores indicative of greater global life satisfaction. The five-item version of the BMSLSS has been found to have acceptable internal consistency when used with adolescents,  $\alpha = .75-.83$  (Funk, Huebner, & Valois, 2006; Ng et al., 2017). Good test-retest reliability has also been found for high school students,  $r = .91$  (Funk et al., 2006). In the current study, internal consistency for the calibration subsample and validation subsample was acceptable,  $\alpha = .80$  and  $\alpha = .82$ , respectively.

**Distress.** Students' self-reported distress was measured by a mean score on the *Social Emotional Distress Survey – Secondary* (SEDS-S; Dowdy, Furlong, Nylund-Gibson, Moore, & Moffa, 2018). The SEDS-S is a 10-item measure used to assess students' self-reported distress in the past month, including anxious and depressed emotional experiences. Items were measured using a four-point response scale (1 = *not at all true of me*, 2, *somewhat true of me*, 3 = *pretty much true of me*, and 4 = *very true of me*). Using a sample of high school students, exploratory and confirmatory factor analyses supported a one-factor solution, with the SEDS-S distress factor demonstrating convergent validity with measures of depression and anxiety and discriminant validity with measures of SWB (Dowdy et al., 2018). Internal consistency for the calibration and validation subsamples was strong,  $\alpha = .92$  and  $\alpha = .92$ , respectively.

### **Demographic Covariates**

To control for differences in gender and cultural backgrounds with a large, heterogeneous sample, self-reported gender, ethnicity, and economic background (i.e., free/reduced lunch status) were specified as covariates and regressed on latent class membership and outcome variables. Demographic information was obtained through self-report on the California Healthy Kids Survey (CHKS; California Healthy Kids Survey, 1999). The CHKS is administered to students in randomly selected schools in grades 4 through 12 across California based on region and size. Student responses were used to obtain a more comprehensive understanding of the relation between students' social, emotional, and behavioral health and their academic performance.



## **Social-Emotional, Substance Use, and Educational Outcomes**

**Social-emotional.** Students' social-emotional strengths were measured by the *Social Emotional Health Survey – Secondary* (SEHS-S), a 36-item self-report measure (Furlong, You, Renshaw, Smith, & O'Malley, 2014). On the version of the SEHS-S adapted for administration by WestEd on the CHKS, items were measured using the same four-point response scale as the SEDS-S (i.e., 1 = *not at all true of me*, 2, *somewhat true of me*, 3 = *pretty much true of me*, and 4 = *very true of me*). A higher order factor structure has been supported by confirmatory factor analyses (CFA) and invariance testing across multiple groups, with 12 subscales loading onto four second-order traits: *Belief-in-Self*, *Belief-in-Others*, *Emotional Competence*, and *Engaged Living* (You, Furlong, Felix, & O'Malley, 2015). Each of the second-order traits loads onto a higher-order trait, termed *Covitality*, or the co-occurrence of social-emotional strengths. Item responses are on a four-point scale (1 = *not at all true of me* to 4 = *very much true of me*). The overall higher-order covitality score was used as an outcome variable. Covitality has been found to significantly predict self-reported SWB and academic achievement and has been found to be negatively associated with symptoms of distress (Furlong et al., 2014). Internal consistency of the 36 items for the calibration and validation subsamples was strong,  $\alpha = .94$ . Depressed emotionality was measured by one item that asks students if they have felt sad or hopeless almost every day for at least two weeks during the past 12 months (0 = *No* and 1 = *Yes*).

**Substance use.** Seven items from the CHKS were used to assess engagement in substance use with cigarettes, alcohol, marijuana, and other drugs in the past 30 days. Response options will be coded on a six-point scale (1 = *0 days*, 2 = *1 day*, 3 = *2 days*, 4 = *3-9 days*, 5 = *10-19 days*, and 6 = *20-30 days*). Student responses which endorsed currently

using alcohol, marijuana, inhalants, or any other illegal drug for 20-30 days in the past month were given a cautionary flag for possible exclusion from the final data set according to criteria for inclusion by WestEd. A mean score for each student was calculated based on responses to the seven items.

**Educational.** Students' sense of school connectedness was measured by five items on the CHKS from the School Connectedness Scale (SCS; McNeely, Nonnemaker, & Blum, 2002; Resnick et al., 1997): "I feel close to people at this school," "I feel like I am part of this school," "I am happy to be at this school," "The teachers at this school treat students fairly," and "I feel safe at my school." Items were measured on a five-point scale (1 = *strongly disagree* to 5 = *strongly agree*). A unidimensional factor structure for these five items has been supported among adolescents in suburban and urban areas (Anderman, 2002), and multigroup invariance has been established across five sociocultural groups ( $N = 500,800$  adolescents, 11 to 18 years of age; Furlong, O'brennan, & You, 2011). Items have demonstrated good reliability,  $\alpha = .78$ . Internal consistency was acceptable for the calibration and validation subsamples,  $\alpha = .83$ .

Students' academic achievement was measured by one item from the CHKS that asked for an overall description of self-reported grades. Item responses were measured on an eight-point scale: 8 = *Mostly A's*, 7 = *Mostly A's and B's*, 6 = *Mostly B's*, 5 = *Mostly B's and C's*, 4 = *Mostly C's*, 3 = *Mostly C's and D's*, 2 = *Mostly D's*, and 1 = *Mostly F's*.

## **Procedure**

In the fall of the 2017/2018 school year, as part of a grant investigating social-emotional health (IES #R305A160157), high school students from five schools in California participated in schoolwide survey administration per an electronic survey as part of the

existing CHKS administration process carried out by WestEd. Administration of surveys is done according to standard procedures set forth by WestEd, including a script for survey proctors. Survey administration procedures were approved by the university institutional review board (IRB). The survey was offered in English and Spanish and was comprised of the CHKS, BMSLSS, SEHS-S, SEDS-S, and the SCS. Information was collected on self-reported gender, race/ethnicity, language classification status (i.e., English Language Learner), home language, and eligibility for free/reduced lunch. Students were required to have passive consent from their parents or caregivers to participate. Data were de-identified according to IRB procedures.

### **Data Analysis Plan**

**Missing data analysis.** Data cleaning procedures involved attention to student assent, severe item missingness, and duplicate survey submissions. As part of the data cleaning process conducted by WestEd, cases were removed that met the criteria for rejection by the CHKS ( $n = 36$ ), including inconsistencies in alcohol or drug use, fictitious drug use, and dishonesty (i.e., respondents who answered that they were not honest on some or hardly any survey questions). Missing value analyses indicated that missing data were likely missing at random (MAR). Cases were included in further analyses if 80% of items on each measure (i.e., BMSLSS, SEDS-S, SEHS, and SCS) were completed. Additional item missingness was accounted for by Full Information Maximum Likelihood (FIML) estimation in *Mplus*. Approximately 93% of the original sample was retained for analyses.

**Latent profile analysis.** To answer the first research question, LPA with FIML estimation using *Mplus* version 7.4 (Muthén & Muthén, 1998-2015) was conducted to explore underlying latent class structure based on adolescents' SWB and distress.

Considering the large sample size of the current study, a split-sample cross-validation procedure was utilized using two approximately equal-sized subsamples of the estimated sample: (a) a calibration data set and (b) a validation data set.

Since LPA allows for the flexibility for item means, variances, and covariances to be uniquely identified for each class (Masyn, 2013), the variance/covariance structure of the model was specified prior to analyses. Given the exploratory nature of the study, four variance/covariance structures were considered. A *class-invariant, diagonal* (Model 1) structure is the default in MPlus and is the most restrictive of the variance/covariance structures, fixing covariances between indicators to zero within classes and constraining variances to be equal across groups. A *class-varying, diagonal* (Model 2) structure fixes covariances between within-class indicators to zero, while variances are freely estimated and allowed to differ across latent classes. A *class-invariant, nondiagonal* (Model 3) structure fixes covariances between indicators to zero and allows covariances between within-class indicators to be freely estimated. Finally, a *class-varying, nondiagonal* (Model 4) structure is the least restrictive, allowing variances to differ across classes and covariances between within-class indicators to be freely estimated.

First, a one class model for each within-class variance-covariance specification was fit to the calibration subsample. The number of classes was increased until indicators of absolute, relative, and substantive fit, as well as conceptual importance and usability, provided evidence for a given number of classes. Since there are no agreed-upon fit statistics to assess model absolute fit with LPA, it was recommended that the overall model-estimated means, variances, covariances, univariate skewness, and univariate kurtosis of the latent class indicator variables be compared to the sample values to assess how well the proposed model

fit the actual data (Masyn, 2013). Based on anticipated sample size, it was anticipated that the statistical analyses could be over-powered, leading to the detection of classes that are not meaningful (Nylund, Asparouhov, & Muthén, 2007). Therefore, classes were examined based on fit statistics and substantive meaning. To assess relative fit between models, Bayesian Information Criterion (BIC), Adjusted BIC, Bayes Factor (BF), Lo-Mendell-Rubin likelihood ratio test (LMR-LRT) and Bootstrap Likelihood Ratio Test (BLRT) were considered to compare  $K$ -classes to  $K-1$ -classes. The lowest values for the BIC and ABIC suggest the best fitting model, although “elbow” plots of BIC and ABIC values were also examined, as diminishing benefit was observed in increasing class number (Masyn, 2013). Significant  $p$ -values for the LMR-LRT and BLRT suggest that the model with  $K$ -classes (i.e., alternative model) fit the data significantly better than the model with  $K-1$  classes (i.e., null model). In addition to fit statistics, model enumeration was based on correct model probability (cmP), or the probability that the number of classes was best given the entire set of models, with any model with a cmP greater than .10 in consideration (Masyn, 2013). Finally, and perhaps of most importance, theoretical rationale was considered, as determining the best model fit based only on fit statistics negates the substantive interpretation of the model and its usefulness within the context of universal mental health screening. Following class enumeration and selection of possible models, entropy and average latent class probabilities were also considered, with a recommended entropy value of .80 or above.

Based on results of the LPA with the calibration subsample, four models with the best fit, model parsimony, and substantive meaning were fit to the validation subsample while fixing all parameters to the estimated values from the final  $K$ -class model. The same criteria utilized to evaluate model fit with the calibration subsample was employed to assess model

fit to the validation subsample. Next, the chosen *K*-class models were fit to the validation subsample while allowing all parameters to be freely estimated. A nested-model likelihood ratio test was used to compare model fit of the *K*-class model with fixed parameter values to the *K*-class model with freely estimated parameters. Masyn (2013) recommended that the *K*-class model is supported across subsamples if there is no significant decrease in model fit between the *K*-class model with fixed parameters and the *K*-class model with freely estimated parameters.

**LPA with distal outcomes.** Following exploration and validation of the underlying latent classes using LPA with an unconditional model, the current study planned to specify a conditional model with covariates and proximal distal outcomes with the validation subsample using a manual BCH three-step approach (Asparouhov & Muthén, 2015; Masyn, 2013). However, LPA with the calibration and validation subsamples did not indicate that any model reliably represented students' item responses in a meaningful way. Therefore, no conditional model with covariates and distals was specified.

## **Results**

### **Latent Class Analyses with the Calibration Subsample**

First, latent profile analysis was carried out with variations in indicators chosen to simultaneously model SWB and distress. Specifically, although measures of SWB and distress were going to be used, different ways of including them in the model were explored (i.e., multiple items or mean composites of multiple items). When determining content and number of indicators, several issues were considered. First, from a statistical perspective the underlying profiles of a latent construct are influenced by the number (i.e., how many there are) and nature (i.e., how they are measured) of indicators chosen to specify the construct.

For example, utilizing 10 items of distress and five items of SWB could potentially skew the emergent latent profiles to be more impacted by distress than SWB simply because there were more distress items. Conversely, utilizing five items of SWB and a single mean score (e.g., average of 5 items) of distress could skew the emergent latent profiles to be more impacted by SWB than distress. To mitigate this issue, profiles based on the five items on the BMSLSS and five items on the SEDS-S were explored. Items demonstrating the highest factor loadings in a previous validation study of the SEDS-S distress factor among high school students were chosen for LPA (Furlong et al., 2018). However, there is limited empirical evidence suggesting using factors scores are an appropriate way to select indicators for LPA models over mean scores.

A final model was explored in which there were two indicators of dual continua mental health: (a) individuals' mean score on the BMSLSS and (b) individuals' mean score on the SEDS-S. Based on results from specifying a *class-invariant, diagonal* variance/covariance structure with each of these models, it was determined that interpretation of classes was maximized when specifying a model with these two indicators. Results showed that the emergent class solutions based on five items on the BMSLSS and five items on the SEDS-S produced solutions almost identical to the solution from the model that only used the mean BMSLSS and the mean SEDS-S scores as indicators. While this was not obvious prior to analyses, the similarity in these results across these two models might be expected when utilizing indicators that measure the same latent construct based on a factor analytic model, as these indicators should be highly correlated to each other. Moreover, considering the practical aims of this study within the context of school-based universal wellness screening, mean scores were favored for ease of use and interpretation. Descriptive

statistics for these indicators for the calibration and validation subsamples can be found in Table 1.

Class enumeration was conducted for all four variance/covariance structures (i.e., Models 1-4) for the two item LPA (mean BLMSS and SEDS-S scores), testing a one-class solution for each Model, and then increasing the number of classes by one until solutions were no longer identified, substantively meaningful, or practically feasible. Across models, there were no clear signals as to the best model based on fit statistics or substantive interpretation (see Table 2). Four models were selected based on some indication of possible model fit, classification probabilities, and substantive interpretation based on previous findings in the context of the DCM.

Based on model fit results for Model 1 (*class invariant, diagonal*), the four-class solution was supported by the  $p$  value of the adjusted LMR, while the five-class solution was supported by the BIC “elbow” plot. Still, the BIC, AIC, and AWE continued to decrease after the six-class solution, but the number of classes was not increased after six due to failed log likelihood convergence, between-class homogeneity, and the small percentage of students making up some of the classes. No clear solutions were supported by the BLRT or BF fit statistics. Fit information for Model 2 (*class varying, diagonal*) suggested a three-class solution fit best based on the LRTS (LRTS = 56.38), adjusted LMR  $p$  value, and BIC “elbow” plot. Fit statistics for Model 3 (*class invariant, nondiagonal*) suggested a four-class solution should be considered based on the  $p$  value of the adjusted LMR and the BIC “elbow” plot, although BIC values continued to decrease. Finally, fit statistics for Model 4 (*class varying, nondiagonal*) supported a three-class solution based on the  $p$  value of the adjusted LMR, and a four-class solution, constraining the variances of the SEDS-S mean



score to be the same for two classes, based on the BIC “elbow” plot. However, neither of these models were considered moving forward due to between-class homogeneity and low rates of log likelihood convergence (30% for the three-class and 12% for the four-class solution), which suggests model instability (see Table 2 for fit statistics for all models tested).

Since there was no definitive solution with which to move forward with validation analyses, all four solutions detailed above were tested with the validation subsample based on procedures recommended by Masyn (2013). Any models that demonstrated replication with the validation subsample would then be examined based on absolute fit to the data and substantive interpretation of results in the context of school-based universal mental health screening.

### **Validation of Class Solutions**

Validation procedures were carried out for each class solution with the validation subsample. First, class solutions were tested by fixing the parameters in the validation subsample to those identified in the calibration subsample. Next, parameters were freed and the same model solutions were tested with the validation subsample again. Finally, the solution with fixed parameters was compared to the solution with free parameters to determine if the difference in model fit was statistically significant based on the nested likelihood ratio test (Masyn, 2013). Nested likelihood ratio tests for all models were significant,  $p < .05$ , indicating that all models fit the validation subsample significantly better when parameters were freely estimated, a result that indicated that the model is not supported in the validation sample. Therefore, none of the solutions identified in the initial class enumeration process with the calibration subsample were replicated with the validation subsample, providing no support for any of the four models considered. Given the paucity of

support for any of the modeling solutions considered (both in the initial and validation sample), and the aims of the current study to explore empirical cut scores to be applied to students' responses on measures of DCM mental health in future universal wellness screening, further analyses were not conducted. Implications of these findings are discussed below.

### **Discussion**

The results of the current study raise questions about the application of LPA with the BMSLSS and SEDS-S as an alternative approach to classification within school-based DCM screening. Model fit criteria did not indicate an obvious “best” model, and none of the chosen models replicated with the validation subsample, which suggests the chosen solutions were not robust to a different subsample. Additionally, proportions of students in similar profiles across class solutions were not always similar and would have very different practical implications if used to identify students most in need of immediate follow-up. The three-class solution in Model 1, for example, indicated that schools would need to follow up with approximately 20% of the calibration subsample (i.e., the class that showed the most distress was 20% of the sample), while the three-class solution in Model 2 indicated that schools would need to follow up with approximately 49% of the calibration subsample. Although Model 2 differed in that it freely estimated variances across classes, the proportion of students in similar profiles (e.g., the class which requires follow up by school professionals) would hopefully remain relatively consistent across models when the number of classes is the same. That is, the signal of the most at-risk students should be mostly robust to the specification of the model and the wide variation in the size of the class indicated it was not. While LPA might have the potential to be a promising approach to classification in this

context, several issues must be explored further to better determine why the model did not fit the data, namely limitations with measurement, sampling and survey context, and methodology.

### **Measurement**

It is possible that one or more of the measures used to assess adolescents' DCM mental health did not provide enough variation in scores to definitively classify students, which can influence model fit indices that are utilized during the class enumeration process. The results of the current study pose questions about the sensitivity of the BMSLSS and SEDS-S, and their utility for differentiating students based on levels of SWB and distress. The SEDS-S was developed as a measure of subsyndromal distress to be used within the school setting, not to diagnose adolescents with clinical levels of symptomatology. Therefore, it is likely that most students endorsed experiencing symptoms of distress to some degree, which is supported by mean scores in both samples indicating that students, on average, reported symptoms of distress to be somewhat true of them (see Table 1). Based on results, it appears that DCM classification with LPA might require measures of SWB and distress to more clearly differentiate students' mental health profiles. It would be worthwhile to explore underlying profiles of DCM with a measure of distress used for more diagnostic purposes to determine if profiles emerge with more within-class homogeneity and between-class differentiation. Still, universal mental health screening has the potential to promote wellness and prevent or identify symptoms of distress *early*. Although a distress measure with more clinical implications might aide in differentiating students, care should also be taken to ensure that measures chosen can differentiate subsyndromal levels of distress and

varying levels of SWB, as these are symptoms that would warrant possible follow up with universal (Tier 1) or targeted (Tier 2) intervention strategies.

### **Sample and Survey Context**

It must be acknowledged that all data were collected within one data sampling context, and this likely influenced study results. First, participants were from the first five schools to participate in anonymous survey administration as part of a large, statewide study. Therefore, the current study cannot ensure that the sample was representative of high school students statewide or nationally. Additionally, administration of DCM measures was done within the existing CHKS administration, which occurs every year. Researchers were not part of the actual administration process and it is unknown if all teachers and staff presented the survey according to WestEd's standard procedures and script. Additionally, since survey responses were anonymous and students were told their classrooms were selected to participate at random, item responses might not be representative of those given in a screening context when students are told that their responses to items might be used to help them individually or as a school. Furthermore, students were tasked with answering dozens of questions about risky behaviors, such as substance use in various settings, prior to answering items on the BMSLSS and SEDS-S, which might have led to fatigue or primed students' attitudes toward the screening process. Although there are idiosyncrasies in any data sampling context, and these data are from randomly selected schools rather than an opportunity sample, it is important to consider the impact of these factors on the present study's aim to identify an empirical approach to classification in the school setting.

### **Methodological**

Within the context of the specification of LPA models, there are several variance and covariance parameters which can be fixed or freely estimated, which gives rise to the testing of multiple models (i.e., Models 1-4). There is a dearth of research on methodological best practices when it comes to choosing which parameters to estimate and constrain, and there is very little guidance on this in the context of classification. Among studies employing LPA for classification within the DCM framework (Kim et al., 2016; Moore, 2017; Rebelez-Ernst, 2015), only Moore (2017) explored variance/covariance structures beyond the *class-invariant, diagonal* model (Model 1), which is the most restrictive of the variance/covariance structures in LPA and the default model in *Mplus*. In addition to Model 1, Moore (2017) also investigated emergent profiles of DCM mental health with a *class-varying, diagonal* variance/covariance structure (Model 2), allowing variances of indicators to differ across classes. Models 3 and 4 were excluded based on the *a priori* assumption that the underlying profiles of mental health account for all shared variation in item response within class (Moore, 2017). In light of the exploratory nature of the present study and lack of guidance for best practices, the current study investigated all variance/covariance structures. However, more information is needed to understand the implications of interpretations of these various models on classification in the school setting, as solutions that break the above *a priori* assumption (i.e., *nondiagonal* structures) but show good model fit would indicate that classes are being influenced by correlations between indicators beyond underlying profiles of DCM mental health (i.e., a relaxation of the conditional independence assumption). For instance, a four-class solution with covariances between indicators freely estimated was identified as a plausible solution. When interpreting results for this solution, shared variation between the BMSLSS mean score and SEDS-S mean score was significant for two of the four classes.

Furthermore, these indicators were positively correlated for one class and negatively correlated with another class, suggesting the relation between SWB and distress is not functioning the same for all students. While this might be the case, more research is needed to better understand what this would indicate about the DCM and the practical application of using these results for classification with LPA in the schools.

### **Future Directions**

More work is needed to better understand if LPA is an appropriate and feasible methodological approach to be used for classification in school-based universal mental health screening, with mental health defined as both the presence of wellbeing and the absence of distress. Considering the time and resources that go into learning LPA and carrying out analyses responsibly, it is likely that classification with LPA will be most plausible and helpful if carried out on a population-based sample of high school students by research teams familiar with the methodology. Then, recommendations can be made to practitioners on classification without practitioners acquiring the tools needed to do these analyses. For example, if a five-class, *class-invariant, diagonal* solution is found to have the best fit to a population-based sample, research might recommend that mean scores and variances defining those classes can be applied to recommend cut scores on the BMSLSS and SEDS-S, with the understanding that there will be some error in classification with any method. Future research should conduct LPA and seek to replicate findings on a large, population-based sample of high school students.

Although LPA might provide a promising empirical alternative to norm-based or criterion-referenced cut scores, there are also possible issues with measurement that must be explored. For LPA to effectively work as a method of classification, the indicators chosen to

model an underlying latent construct (e.g., DCM mental health) must be able to differentiate classes that are well separated from each other and homogenous within class (Masyn, 2013). Considerations must be given to utilizing measures of SWB and distress that differentiate students but are also palatable to schools responsible for follow-up care. Ideally, classification of students based on their mental health would better enable schools to make decisions about universal, targeted, and intensive (Tier 3) intervention approaches, which is in line with multitiered systems of supports. Therefore, measures should differentiate those currently experiencing optimal levels of wellness, those who are at-risk of experiencing social-emotional difficulties in the future due to either higher levels of distress or lower levels of SWB, and those who are currently experiencing more severe social-emotional problems due to both high levels of distress and low levels of SWB. Although this might be reminiscent of deficit-based screening, different students will be identified in all groups by asking about both SWB and distress. For example, some students who might have been considered “troubled” in problem-focused screening will also endorse high levels of SWB that will perhaps allow school teams to follow up with fewer resources than for students with low levels of SWB and high levels of distress.

As research continues to explore the utility of LPA as a classification approach in universal mental health screening, it might be beneficial to further explore this approach in the context of universal screening, rather than annual anonymous survey administration, as student responses to items might differ. Additionally, future research examining LPA for classification should continue to employ a calibration/validation procedure if number of participants allows for it. Previous research utilizing LPA in the context of DCM mental health with adolescents did not attempt to replicate findings with a subsample or independent

sample of students, and these studies' findings were not replicated in the current study. While this brings up questions about validity of previous findings, it is also possible that the measures chosen in previous studies allowed for better differentiation, and future research should explore LPA with calibration and validation samples using previously utilized measures. Overall, continued exploration of LPA is necessary before recommendations on classification can be responsibly made to schools engaging in universal screening efforts with measures of SWB and distress.



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Table 1

*Variable Descriptive Statistics and Correlations for Indicators of DCM Mental Health for Calibration and Validation Subsamples*

Variables	BMSLSS	SEDS-S	<i>M</i>	<i>SD</i>
BMSLSS Mean Score	-		4.52 (4.47)	1.02 (1.07)
SEDS-S Mean Score	-.46* (-.49*)	-	2.08 (2.08)	0.85 (0.84)

*Note.* Scores in parentheses represent statistics for the validation subsample. BMSLSS = Brief Multidimensional Student Life Satisfaction Scale, range 1-6. SEDS-S = Social Emotional Distress Survey – Secondary, range 1-4.

\* $p < .01$ .

Table 2

*Fit Statistics for Models 1 through 4 with the Calibration Subsample*

Model	Number of Classes	Log	BIC	<i>p</i> value	<i>p</i> value	BF	cmP	Entropy
		Likelihood		of LMRT	of BLRT			
<b>Model 1</b>	1-class	-6258.154	12547.3139			4.9134E-191	0	
	2-class	-5808.325	11670.9103	<.001	<.001	7.66219E-48	3.666E-147	.804
	3-class	-5688.21	11453.9348	<.001	<.001	1.37452E-34	4.784E-100	.789
	4-class	-5598.613	11297.9952	<b>&lt;.001</b>	<.001	8.91831E-34	3.4808E-66	.826
	5-class	-5510.886	11145.7956	.0342	<.001	9.00468E-18	3.903E-33	.800
	6-class	-5460.01	11067.298	.0033	<.001	4.33436E-16	4.3344E-16	.827
	7-class	<b>-5413.008</b>	<b>10996.5485</b>	.075	<.001	0	<b>1</b>	.831
<b>Model 2</b>	1-class	-6257.154	12545.343			9.259E-302	0	
	2-class	-5544.602	11159.0328	<.001	<.001	3.16508E-62	3.1396E-91	.726
	3-class	-5383.597	10875.8166	<b>.0058</b>	<.001	3.14254E-06	9.9194E-30	.712
	4-class	-5355.409	10850.4757	.0167	<.001	1.06131E-13	3.1565E-24	.748
	5-class	-5306.138	10790.7275	a	a	2.97415E-11	2.9741E-11	.679
	6-class	<b>-5266.382</b>	<b>10742.2505</b>	a	a	0	<b>1</b>	.772
<b>Model 3</b>	1-class	-5975.746	11990.2494			9.566E-103	1.338E-211	
	2-class	-5725.335	11520.4333	<.001	<.001	6.68954E-54	1.399E-109	.809
	3-class	-5587.393	11275.5552	<.001	<.001	1.16126E-30	2.0909E-56	.851
	4-class	-5502.962	11137.6991	<b>.0011</b>	<.001	4.09484E-15	1.8006E-26	.808
	5-class	-5454.33	11071.441	.119	<.001	4.39722E-12	4.3972E-12	.792

100

	6-class	<b>-5412.677</b>	<b>11019.1409</b>	.0136	<.001	0	<b>1</b>	0.791
	1-class	-5975.746	11990.2494			2.8074E-198	5.212E-264	
	2-class	-5497.612	11080.4902	<.001	<.001	2.45996E-23	1.8565E-66	.674
<b>Model 4</b>	3-class	-5426.174	10976.3716	<b>.0158</b>	<.001	1.37046E-32	7.5468E-44	.752
	4-class <sub>b</sub>	-5329.552	10829.6365	.071	<.001	3.87271E-09	5.5068E-12	.745
	5-class <sub>c</sub>	-5290.804	10790.8978	.2015	<.001	.001423963	.00142194	.720
	6-class <sub>d</sub>	<b>-5264.871</b>	<b>10777.7892</b>	.9967	<sub>a</sub>	0	<b>0.99857806</b>	.697

*Note.* Bolded values indicate preferred model for a given fit index. Rows in boxes indicate class solution selected for each model. <sub>a</sub> Likelihood ratio test could not be computed when comparing values to the previous *k*-class solution since different variances were fixed between models. <sub>b</sub> Variance of the SEDS-S mean score was fixed for class 3 and 4. <sub>c</sub> Variance of SEDS-S mean score was fixed for classes 2, 3, and 4. <sub>d</sub> Variance of the SEDS-S mean score was fixed for classes 1, 2, and 3; Variance of BMSLSS mean score was fixed for classes 1 and 6.



## **Moving the Field Forward: Classification in DCM Screening**

The current studies examined two approaches to classification of high school students' responses to measures of SWB and distress in the context of universal DCM screening in the schools. Although previous DCM literature with adolescents demonstrated that there is value in asking students about both their distress and SWB, research that develops optimal cut scores on DCM measures is now needed to improve practical applications. This dissertation sought to identify optimal cut scores on one measure of SWB, the BMSLSS, and one measure of distress, the SEDS-S, in an effort to move the field of DCM screening forward.

In Study 1, ROC curve analysis was utilized to identify optimal cut scores on the BMSLSS and SEDS-S that predicted positive mental health “diagnoses” on the MHC-SF. Findings indicated that optimal cut scores created meaningful groups of students based on their DCM mental health, and these groups had significantly different levels of co-occurring strengths, school connectedness, overall life satisfaction, and depressed emotionality. As expected, outcomes favored students who met the cut scores on both measures for *flourishing mental health*, followed by *moderately mentally healthy*, and then *languishing*. While cut scores identified with ROC curve analysis proved to be meaningful, there were also some limitations to the study. Classification accuracy of the SEDS-S distress measure was not optimal, and PPV of the SEDS-S for classifying *languishing* students was lower than desired, which meant there were many false positive cases in the *languishing* group. In the absence of a “gold standard” for positive mental health, or wellness, diagnoses from the MHC-SF were used as criteria for cut scores. It is possible that different cut scores would be identified with a different criterion measure or a different objective for screening. Overall, results of Study 1

were a promising first step in improving the feasibility and practicality of universal DCM screening in the schools, but more work is needed to continue developing cut scores for diverse populations and school priorities.

With a goal of examining the utility of a more empirical approach to classification, Study 2 explored the potential to use latent profiles of students' DCM mental health to inform cut scores on the BMSLSS and SEDS-S. However, a class-solution with good fit and theoretical rationale was not replicated, which highlighted the need for continued work in this area. Similar to limitations in Study 1, it is possible that measures used did not adequately differentiate students, particularly on levels of distress. Additionally, more work is needed to better understand the practical implications of each variance/covariance model, as preliminary investigations in Study 2 might suggest that relations between SWB and distress vary based on DCM profile. Given the potential of LPA to inform cut scores that are free from assumptions of a normative distribution and are not based on a criterion outcome, exploration into these limitations is worthwhile.

Findings from Study 1 and Study 2 highlight needed directions in the field of school-based universal DCM screening. Previous literature has outlined the major steps for schools to take when implementing this type of screening: (a) identify the key participants and plan, (b) select screening instruments, (c) obtain consent, (d) administer the instruments, (e) score and analyze the screening data, and (f) follow-up (Moore et al., 2015). The current studies demonstrate the need for additional work at several steps of the screening process in order to increase and improve implementation by schools. While continued development at each step is warranted, this discussion will focus on steps one, two, five, and six.

### **Step One: Identify the Key Participants and Plan**

Moore and colleagues stressed the need for school screening teams to thoughtfully and intentionally set the objectives for screening prior to following through with any other steps (2015). While asking students about their wellness and distress is important for any screening objective, objectives of screening may vary across schools, with some conducting screening to gauge school climate, others seeking to identify students at-risk of social-emotional difficulties early, and others wanting to identify a small percentage of students definitively in need of Tier 2 services. Each of these objectives is meaningful, but schools must keep their objectives in mind at each subsequent step of the screening process. The cut scores identified in Study 1 would likely aid schools in screening for wellness and perhaps early identification practices, as students were classified as *languishing* who were experiencing lower levels of SWB than their peers and higher subsyndromal symptoms of distress. For schools that do not have the capacity to follow through with early identification, or their base rates of students at-risk exceed their allotted resources for follow-up, they may set objectives to be more stringent and identify fewer students for follow-up care, which would impact the criterion measure used to find optimal cut scores on measures of SWB and distress. Schools must also decide the frequency in which they will conduct screening (Kilgus & Eklund, 2016), as this will influence objectives of screening at each iteration. For instance, schools that implement screening practices more than once per academic year may choose to identify fewer students at their second or third screening than their first, which would impact cut scores and measures used. Future research should investigate optimal cut scores given different objectives for screening and at different time points in the year in order to meet the changing needs of schools and the limited availability of resources.

### **Step Two: Select Screening Instruments**

Schools' objectives for screening, in addition to students being served and resources that can be dedicated to survey administration, should help guide their selection of DCM measures (Moore et al., 2015). Literature for screening in the schools recommends that measures demonstrate empirical support based on reliability and validity estimates, as well as diagnostic accuracy (Glover & Albers, 2007; Kilgus & Eklund, 2016). The measures used in the current studies showed acceptable to good diagnostic accuracy for identifying positive mental health diagnoses in Study 1, but results from both studies suggest that measures developed to better differentiate SWB and distress levels might be useful depending on school's objectives for screening. Still, schools must balance other factors when selecting measures, including the appropriateness of measures for a school's population, cost, brevity of administration, and the relation of chosen instruments to other constructs of interest. Measures will vary based on outcomes schools would like to predict, such as wellness, academic achievement, and severe distress. Given the findings of Study 2, more work is also needed to understand if classes of DCM mental health are robust enough that the measures chosen to assess SWB and distress do not change the class solutions. This will be paramount in determining the utility of LPA to inform cut scores for school practitioners conducting DCM screening.

#### **Step Five: Score and Analyze the Screening Data**

In an effort to address some of the practical barriers to implementation of universal DCM screening and improve follow-up strategies, the current studies focused on finding cut scores that allow practitioners to score data and make accurate classification decisions based on objectives for screening. Currently, many schools administer commercially-available screening products with researcher-defined cut scores for classification, which might not

optimally differentiate students' social-emotional wellbeing or be substantively meaningful for some school's screening objectives. Some schools conducting universal DCM screening consult or collaborate with agencies or local universities to score and analyze results and classify students (Moore et al., 2015). However, these partnerships are not available to all school districts, and classification with cut scores might enable schools to implement screening administration without outside support. The current studies chose measures that are freely available and easy to administer and score, which can minimize resources needed for staff trainings and scoring software. Even with these choices, it is possible that schools would need to adjust cut scores on the BMSLSS and SEDS-S depending on screening objectives, base rates, and resources for follow-up services (Moore et al., 2015). It is also important to recognize that brief measures of social-emotional health for youths, like the BMSLSS, have been available to practitioners for several years without many schools administering them to students. More collaborative research with school teams is needed to better understand how measures are chosen by school practitioners and what type of scoring procedures are preferred in the context of screening.

### **Step Six: Follow-up**

Literature recommends that follow-up services should occur as soon as possible (Moore et al., 2015), which necessitates appropriate classification approaches with measures of SWB and distress. Schools must be thoughtful in understanding their available resources for individual, group, and schoolwide follow-up services, which will inform how many students they can serve. In turn, this influences measures used, optimal cut scores, and criterion measures to create or validate those cut scores. Implications from Study 1 suggested that follow-up services with the identified cut scores on the BMSLSS and SEDS-S would

likely involve more data collection that assesses specific strengths, areas of distress, and coping skills, which would aid schools in adequately serving students with available resources. However, if a school knew that they could only follow-up with students most in need, they may elect to use more stringent cut scores or a criterion measure that is more distress focused. One of the possible advantages of LPA is that groups are formed based on common patterns of item responses. This might allow schools to see more specific profiles of students and implement targeted strategies based on the profiles that emerge in the first gate of screening, rather than imposing cut scores based on a dichotomous outcome on measures with only adequate sensitivity and specificity.

The utility of school-based universal mental health screening and the value of asking students about their SWB and distress have been highlighted across contemporary screening literature. It is time for research to address the barriers to implementation so that multitiered systems of support can be realized across school districts, as every student deserves a chance to be well. The present studies took one step toward bridging research to practice by investigating two different ways to classify students based on DCM measures of mental health. Still, more research and collaboration are needed at each step of the screening process to make DCM screening a plausible, helpful resource for schools.

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