**Title**
A Longitudinal Investigation of Dual-Factor Mental Health in Adolescence




**Author**
Moore, Stephanie Anne



**Publication Date**
2017

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Santa Barbara

# A Longitudinal Investigation of Dual-Factor Mental Health in Adolescence

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

by

Stephanie Anne Moore

Committee in charge:

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

September 2018

The dissertation of Stephanie Anne Moore is approved.

Michael Furlong

Karen Nylund-Gibson

Erin Dowdy, Committee Chair

June 2017

A Longitudinal Investigation of Dual-Factor Mental Health in Adolescence

VITA OF STEPHANIE ANNE MOORE
June 2017

## EDUCATION

September 2018 (expected) **University of California, Santa Barbara**
Ph.D. in Counseling, Clinical, and School Psychology
Emphasis in School Psychology
Advisor: Erin Dowdy, Ph.D.

June 2016 **University of California, Santa Barbara**
Master of Education (M.Ed.)

June 2013 **University of California, Los Angeles**
B.A. in Psychology, 2013
Summa Cum Laude

## RESEARCH EXPERIENCE

**Dissertation Research** September 2013 - Present
Title: *A Longitudinal Investigation of Dual-Factor Mental Health in Adolescence*

- Collected longitudinal schoolwide screening data for a cohort of adolescents followed from grade 9 (2013) to grade 12 (2016) and from grade 10 (2013) to grade 12 (2015).
- Facilitated onsite data collection through paper-and-pencil and electronic survey administration for approximately 2,000 students each school year (approximately 800 of which were the focus of the current project).
- Designed research questions and data analysis procedures, including collection of mental health, academic, and prosocial behavior survey data.
- Manage 4-year longitudinal dataset.
- Perform advanced structural equation analyses, including latent profile analysis and latent transition analysis.
- Results to be presented in two culminating dissertation manuscripts submitted for publication, and shared with the school at which primary data-collection occurred.

*Chair: Erin Dowdy, Ph.D.*
*Committee Members: Michael Furlong, Ph.D., Karen Nylund-Gibson, Ph.D.*

**Graduate Student Researcher** September 2013 – June 2017
***Center for School Based Youth Development*** *(Approximately 10 Hours/Week)*
*University of California, Santa Barbara*

- Facilitate implementation and evaluation of a U.S. Department of Education, Institute for Education Sciences grant to evaluate the psychometric properties of the Social Emotional Health Survey – Secondary, and its usefulness as a universal screening tool.
- Maintain four-year longitudinal database of schoolwide mental health screening data.
- Aid with development of user manual and related materials for Social Emotional Health Survey and for distribution to school personnel.

- Organize, distribute, and administer screening instruments to teachers and students as part of universal screening for complete mental health; collect and analyze data.
- Supervise research assistants and undergraduate research projects.

*Advisor: Erin Dowdy, Ph.D. & Michael Furlong, Ph.D.*

**Project Coordinator** June 2015 –July 2017
***Check, Connect, & Respect Mentoring Program*** *(Approximately 10 Hours/Week)*
*University of California, Santa Barbara & Santa Barbara Unified School District*

- Train undergraduate student mentors and provide weekly training, instruction, and supervision.
- Coordinate high school student referrals to the program via universal screening and teacher/counselor referral.
- Develop and organize measures for data collection and program evaluation; evaluate implementation and success of intervention on participants' social-emotional and academic well-being.
- Manage university human subjects research approval.

*Advisor: Erin Dowdy, Ph.D.*

**Graduate Student Researcher** January 2016 – September 2016
***Project Act Early*** *(Approximately 5 Hours/Week)*

- Assisted with U.S. Department of Education, Institute for Education Sciences grant to evaluate the psychometric properties of the BASC-2 Behavioral Emotional Screening System.
- Aided with teacher and family recruitment, data collection, and dissemination of reports.
- Consulted on database set up and organization.

*Advisor: Erin Dowdy, Ph.D., & Randy W. Kamphaus, Ph.D.*

**Graduate Student Researcher** April 2016 – June 2016
***Santa Barbara County Probation Department*** *(Approximately 10 Hours/Week)*
*University of California, Santa Barbara*

- Analyzed and interpreted data collected as part of an evaluation of evidence-based community corrections programs as part of probation services under Senate Bill 678.
- Presented results of program evaluation in a culminating technical report.

*Advisor: Jill Sharkey, Ph.D.*

**Graduate Student Researcher** August 2014 – March 2016
***First 5 Santa Barbara County Evaluation*** *(Approximately 10 Hours/Week)*
*University of California, Santa Barbara*

- Collected, analyzed, and interpreted data from community intervention and resource programs and presented results of analyses via annual evaluation report and bi-yearly evaluation meetings.
- Consulted with community partners and program leaders on measure selection and design to assess target outcomes.
- Designed survey to measure participant progress toward bachelor degree.

*Advisor: Erika Felix, Ph.D.*

**Undergraduate Research Assistant** June 2012 – June 2013
***Child Focus on Innovation and Redesign in Systems and Treatment (FIRST) Lab*** *(Approximately 8 Hours/Week)*
*University of California, Los Angeles*

- Aided in management of treatment progress data and therapist data for a randomized controlled trial of an effectiveness study comparing modularized manual treatment with usual care for youth with anxiety, depression, trauma, or conduct disorders.
- Developed database for interpreting client progress data and use of clinical dashboards.
- Coded therapy sessions; developed coding manual for deviations from treatment integrity; trained research assistants in coding procedure.

*Advisor: Bruce Chorpita, Ph.D.*

**Undergraduate Research Assistant** April 2012 – June 2013
***Center for Mental Health in Schools*** *(Approximately 8 Hours/Week)*
*University of California, Los Angeles*

- Managed online resource database and database of newsletter recipients.
- Developed resources for parents, practitioners, and scholars regarding AD/HD, prevention, and early intervention in school.

*Advisor: Howard Adelman, Ph.D. & Linda Taylor, Ph.D.*

## PUBLICATIONS

Dowdy, E., Harrell-Williams, L. M., Dever, B. V., Furlong, M. J., **Moore, S. A.,** Raines, T. C., & Kamphaus, R. W. (2016). Predictive validity of a student self-report screener of behavioral and emotional risk in an urban high school. *School Psychology Review, 45*(4), 458-476. doi:10.17105/SPR45-4.458-476

**Moore, S. A.,** Dowdy, E., & Furlong, M. J. (2016). Using the Depression, Anxiety, Stress Scale – 21 with U.S. adolescents: A competing models analysis. *Journal of Psychoeducational Assessment.* doi:10.1177/0734282916651537

**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*. Advanced online publication. doi:10.1007/s40688-015-0062-x

**Moore, S. A.,** & Dowdy, E. (2015). Safety, policies for ensuring. In Scarlett, W. G. (Ed.), *Classroom Management: An A-Z Guide* (pp. 687-689). Thousand Oaks, CA: Sage Publications.

### Newsletters & Practitioner Resources

**Moore, S. A.**, Adelman, H.S. & Taylor, L. (2013). Barriers to prevention in schools: Prevention policy implementation barriers. Retrieved from http://smhp.psych.ucla.edu/pdfdocs/prevseriespolicybarr.pdf

**Moore, S. A.**, Adelman, H.S. & Taylor, L. (2013). Barriers to prevention in schools: A look at what's happening. Retrieved from http://smhp.psych.ucla.edu/pdfdocs/preventseriespolicy.pdf

**Moore, S. A.**, Adelman, H.S. & Taylor, L. (2013). Preventing student problems: What are the barriers? Retrieved from http://smhp.psych.ucla.edu/pdfdocs/preventseriesintro.pdf

**Moore, S. A.**, Adelman, H.S. & Taylor, L. (2012). Attention Deficit Disorder (ADHD) and schools: Outline focused on key questions and concerns. Retrieved from http://smhp.psych.ucla.edu/pdfdocs/adhd-outline.pdf

**Moore, S. A.**, Adelman, H.S. & Taylor, L. (2012). Questions parents ask and some concerns about Attention Deficit/Hyperactivity Disorder (ADHD). Retrieved from http://smhp.psych.ucla.edu/pdfdocs/adhdpar.pdf

### Technical Reports

**Moore, S.**, & Dowdy, E. (2017). Evaluation of the Check, Connect, and Respect Mentoring Program at San Marcos High School: 2015-2016. Report submitted to Santa Barbara Unified School District and San Marcos High School.

Stein, R., Sharkey, J. Dowdy, E., & **Moore, S.** (2016). Evaluation of the Check, Connect, and Respect Mentoring Program at San Marcos High School: 2014-2015. Report submitted to Santa Barbara Unified School District and San Marcos High School.

Wroblewski, A., **Moore, S.,** Eusterbrock, M., Mayworm, A., & Sharkey, J. (2016). Evaluation of the Community Corrections Performance Incentive Act (SB678) in Santa Barbara County. Report submitted to Santa Barbara County Department of Probation.

Felix, E. D., Terzieva, A., M. J., **Moore, S**., Meskunas, H., & Quirk, M. (2016). First 5 Santa Barbara County Evaluation Report 2014-2015. Report submitted to First 5 Santa Barbara County.

Felix, E. D., Terzieva, A., M. J., Quirk, M., & **Moore, S**. (2015). First 5 Santa Barbara County Evaluation Report 2013-2014. Report submitted to First 5 Santa Barbara County.

## PRESENTATIONS

**Moore, S. A.,** Dowdy, E., DiStefano, C., Greer, F., & Pompey, K. (February 2017). Screening in preschool using the BASC-3 Behavioral Emotional Screening System. Poster presented at the National Association of School Psychologists Annual Convention. San Antonio, TX.

Bertone, A., Dowdy, E., Furlong, M. J., **Moore, S. A.**, Carnazzo, K., Moffa, K., & Garcia, M. G. (February 2017). Implementing universal complete mental health screening in high schools. Mini-Skills workshop presented at the National Association of School Psychologists Annual Convention. San Antonio, TX.

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 21st Annual Conference on Advancing School Mental Health. San Diego, CA.

**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.

**Moore, S. A.,** Dowdy, E., Furlong, M., Dever, B., Harrell-Williams, L., Raines, T., … & Bovery, B. (February 2016). Universal self-report screening in high school to predict internalizing symptoms. Presented at the National Association of School Psychologists Annual Convention. New Orleans, LA.

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

Stein, R., Swami, S., & **Moore, S. A.** (February 2016). Check, Connect, and Respect: Reducing dropout and increasing school engagement. Presented at the National Association of School Psychologists Annual Convention. New Orleans, LA.

**Moore, S.A.,** Widales-Benitez, O., Carnazzo, K., Kim, E., Orellana, G., Dowdy, E., & Furlong, M. (February 2015). Best Practices in Universal Complete Mental Health Screening.  Presented at the National Association of School Psychologists Annual Convention. Orlando, FL.

Carnazzo, K.W., **Moore, S.,** Dowdy, E., Widales-Benitez, O. (February 2015). Schoolwide Behavioral and Emotional Health Screening: Legal and Ethical Considerations. Presented at the National Association of School Psychologists Annual Convention. Orlando, FL.

Mayworm, A. M., Kim, E. K., Babcock, S. B., & **Moore, S. A.** (February 2015). Evaluation of Check, Connect, and Respect with college undergraduate mentors. Poster presented at the National Association of School Psychologists Annual Convention. Orlando, FL.

**Moore, S. A.,** Mendez, S. E. A., & Widales-Benitez, O. (October 2014). Learn, Act, and Train Others to Support LGBTQ Youth in Schools. Presented at the Convention of the California Association of School Psychologists, San Diego, CA.

Park, A. L., **Moore, S. A.,** Cho, E., Greenberg, S., Lang, L., Vich, K., Regan, J., Guan, K., Reding, M., Chorpita, B. F., & Weisz, J. R. (2013). Treatment integrity issues within community mental health settings. Poster accepted for presentation at the 47th Annual Convention of the Association of Behavioral and Cognitive Therapies, Dissemination and Implementation Special Interest Group Exposition, Nashville, TN.

Brown, T. E., Park, A. L., **Moore, S. A.**, & Chorpita, B. F. (2012). How much is enough? Identifying clinically-relevant information for decision-making models. Poster accepted for presentation at the 46th Annual Convention of the Association of Behavioral and Cognitive Therapies, Dissemination and Implementation Science Special Interest Group Exposition, National Harbor, MD.

## CLINICAL/PRACTICUM EXPERIENCE

**Advanced Practicum Student** August 2016 – June 2017
**San Marcos High School, Santa Barbara, CA** *(Approximately 10 Hours/Week)*

- Provide individual counseling to students in grades 9 to 12 with presenting problems related to depression, autism, conduct, and learning difficulties. Targeted goals include reducing depressive symptoms, promoting positive self-assessments and esteem, promoting resiliency and efficacy in school-work completion, building social skills, building coping skills, and self-management.
- Utilize cognitive-behavioral and solution focused approaches in counseling.
- Monitor progress toward counseling goals using standardized rating scales, youth self-report measures, teacher report measures, and observation.
- Administer and score comprehensive psychoeducational evaluations, including intelligence, cognitive processing, and social-emotional measures.
- Complete classroom observations and parent, teacher, and student interviews.
- Write comprehensive reports, including academic assessment data, and present at Individualized Education Program (IEP) meetings.

*Supervisor: Emily Pariseau, M.Ed., PPS, & Erin Dowdy, Ph.D.*

**Advanced Practicum Student** September 2016 – June 2017 *(Hours Variable)*
**Learning Tree Preschool, Goleta, CA** March 2016 – July 2016 *(Approximately 4 Hours/Week)*
August 2014 –June 2015 *(Approximately 8 Hours/Week)*

- Administer, score, and interpret comprehensive psychoeducational evaluations, including intellectual, neuropsychological, cognitive processing, social-emotional, and adaptive behavior assessments with preschool-age and private school elementary-age students.

- Complete school and home observations of children and conduct parent, teacher, and student interviews as part of comprehensive assessment. Information is compiled into integrated reports presented at IEP meetings.
- Consult with preschool staff to address student behavior and promote learning. For example, provided twice-weekly consultation using a behavioral consultation model to a preschool teacher to manage behavioral outbursts, impulsivity, and inappropriate social behavior in a 4 year old male student.
- Consulted with private school teachers regarding academic difficulties and behavioral interventions. For example, provided behavioral consultation to address manifestations of inattention, hyperactivity, and impulsivity in the classroom for a 6$^{th}$ grade male student.
- Conducted weekly social skills group using Second Step curriculum for preschool students.
- Facilitated play and development of social skills on the playground, as well as supported academic behaviors in the classroom with preschool students.
- Participated in Student Success Team meetings with parents, teachers, and coordinating service staff to triage referrals for assessment or intervention.

*Supervisor: Judy Senning-Brown, M. S., PPS, Jill Sharkey, Ph.D., NCSP, & Erin Dowdy, Ph.D.*

**Graduate Student Clinician** April 2016 – November 2016
**Psychological Assessment Center** *(Hours Variable)*
**University of California, Santa Barbara, CA**

- Administer, score, and interpret psychological and neuropsychological assessments as part of integrated, comprehensive evaluations for two adolescent clients referred for assessment by their families. Presenting problems included attention/hyperactivity, depression, anxiety, and academic difficulties.
- Conduct semi-structured intake interviews to identify presenting problems and gather background information on clients.
- Provide evaluation results to families in written format via integrated psychological reports and scheduled feedback sessions.

*Supervisor: Erik Lande, Ph.D.*

**Advanced Practicum Student** October 2015 – June 2016
**Ellwood Elementary School, Goleta, CA** *(Approximately 8 Hours/Week)*

- Provided individual psychotherapy to students with emotional disturbances related to anxiety and depression and with attention deficit/hyperactivity symptoms as part of the center for therapeutic education (CTE) and special education services.
- Provided small-group counseling to build positive social skills and support friendship among 3$^{rd}$ grade girls.
- Performed comprehensive evaluations, including intellectual, cognitive processing and, social-emotional assessments; observations; and parent, teacher, and student interviews. Wrote comprehensive, integrated reports presented at IEP meetings to inform education and treatment planning.
- Provided behavioral and social-emotional consultation to teachers and parents.

*Supervisor: Joe Isaacson, M.Ed., PPS & Erin Dowdy, Ph.D.*

**Mental Health Externship Student** September 2015 – June 2016
**Los Berros Elementary School, Lompoc, CA** *(Approximately 10 Hours/Week)*

- Provided weekly individual psychotherapy as well as behavioral and academic intervention services for students with severe emotional dysregulation within a school-based center for therapeutic education (CTE). The CTE program is designed for students with emotional and behavioral difficulties and includes positive behavior supports, token economies, and explicit instruction in emotion regulation and behavior management.
- Utilized cognitive behavioral techniques, mindfulness, person-centered, and solution-focused approaches with children between ages 7 and 10 years whose presenting problems included depression, generalized anxiety, childhood bipolar, behavior/conduct problems, and emotion regulation problems.
- Implemented weekly group counseling aimed at promoting development of positive social skills using evidence based curricula (e.g., Second Step, PATHS).
- Provided behavioral and social-emotional consultation to teachers and classroom aids.

*Supervisor: Travis Jenkins, Ed.S., PPS & Erin Dowdy, Ph.D.*

**Practicum Student** January 2015 – June 2015
**Monroe Elementary School, Santa Barbara, CA** *(Approximately 8 Hours/Week)*

- Performed comprehensive psychoeducational evaluations, including administration of intellectual, cognitive processing, social-emotional, and adaptive behavior assessments; observations; and parent, teacher, and student interviews. Information was compiled into comprehensive reports presented at IEP meetings.
- Primary presenting problems included academic challenges, behavioral dysregulation, and social-skills deficit for students with learning disorders, autism, intellectual disability, and depression.

*Supervisor: Lauren Meier, M.A, PPS; Melissa Quigley, Ed. S., PPS; & Jill Sharkey, Ph.D.*

**Psychology Practicum** January 2013 – June 2013
**Hosford Clinic, Santa Barbara, CA** *(Approximately 10 Hours/Week)*

- Provided individual psychotherapy to college-aged students, including administration of rating scales (Outcome Rating Scale, Session Rating Scale, Subjective Well Being scale, Working Alliance Inventory).
- Participated in weekly supervision during which videotaped sessions were reviewed.

*Supervisor: Heidi Zetzer, Ph. D.*

**Graduate Student Mentor** October 2013 – June 2014
**San Marcos High School, Santa Barbara, CA** *(Approximately 5 Hours/Week)*

- Provided small group and individual academic support and assisted with classroom management.
- Provided weekly mentorship for students as part of the Check, Connect, and Respect mentoring program, including a focus on building self-advocacy skills, academic behaviors, and attendance via motivational-interviewing.
- Co-facilitated weekly social skills intervention for four adolescents with autism spectrum disorders.

*Supervisor: Beth Laurie, M.Ed., PPS; Ashley Mayworm, M.Ed.; & Erin Dowdy, Ph.D.*

## TEACHING EXPERIENCE

**Course Supervisor** **University of California, Santa Barbara**

- Fall, Winter, Spring 2015-16, 2016-2017 *Counseling, Clinical, and School Psychology Department* (CNCSP)
  - Provide weekly training to undergraduate mentors, in the form of didactic presentations, and supervision regarding high-school student mentees.

**Teaching Associate** **University of California, Santa Barbara**

- Summer 2016 Research Methods in Applied Psychology, *CNCSP*

**Teaching Assistant** **University of California, Santa Barbara**

- Summer 2015 College Student Peer Helping, *CNCSP*
- Spring 2015 Internship in Professional Psychology, *CNCSP*
- Fall 2014 Cognitive Assessment, *CNCSP*
- Spring 2014 Identity and Pluralism, *CNCSP*

**Guest Lecturer** **University of California, Santa Barbara**

- Spring 2017 Research methods in Applied Psychology, *CNCSP*
  - Provided a guest lecture on the topic of dual-continua mental health, including existing research support, developing work, and the impact of research on practice
- Spring 2017 The School Psychologist as the Intervention Consultant: School Psychology Practicum, *CNCSP*
  - Provided a guest lecture on the topic of preschool and early childhood special education law, assessment, and intervention
- Winter 2017 Positive Psychology Across the Lifespan, *CNCSP*
  - Provided a guest lecture on the topic of a tier-2 mentoring intervention to promote adolescent social-emotional strengths
- Winter 2016 & 2017 Factor Analysis, *Education Department*
  - Provided a guest lecture on the topic of computing statistics for bifactor models
- Spring 2014 Identity and Pluralism, *CNCSP*
  - Provided two guest lectures on exceptional identities (i.e., individuals of gifted status or with disabilities)

**Undergraduate Course Assistant** **University of California, Los Angeles**

- Spring 2013 Learning Problems, Schooling Problems, Policy and Practice

## RELEVANT WORK EXPERIENCE

**Statistics Software Support Consultant** July 2015 – June 2017
*Information Technology Group, Gevirtz Graduate School of Education, University of California, Santa Barbara*
Supervisor: William Doering

- Provide statistics and statistical software support to graduate students for research projects and course assignments.
- Software packages include SPSS, M*plus*, and Microsoft Excel.

**Student Assistant** October 2013 – March 2014
*Hosford Counseling and Psychological Services Clinic, Santa Barbara, CA*
Supervisor: Dyan Wirt

- Greeted and checked-in clients for psychotherapy and psychiatric appointments**,** collected payment for services and recorded in online data-management system**,** answered telephone calls and responded to prospective clients' questions regarding services offered

**Activity Leader II** February 2009 – September 2013
*Saugus Union School District*, *Santa Clarita*, *CA*
Supervisor: Jane Jorgensen, Emilie Villaflor

- Promoted social, emotional, physical, and cognitive growth of the children while creating a warm, caring, and stimulating environment
- Assisted with plans, organization, and implementation of age-appropriate enrichment activities that meet both the individual and the developmental needs of the children

## PROFESSIONAL SERVICE

Student Representative on the board for the Central Coast Association of School Psychologists, Santa Barbara, CA August 2016 – Present
Admissions Committee Member, Department of Counseling, Clinical, School Psychology, UCSB September 2015 – June 2016
Assistant Reviewer, *Journal of Psychoeducational Assessment.* April 2015 – Present
Climate Committee Member, Department of Counseling, Clinical, School Psychology, UCSB September 2014 – June 2015
Assistant Reviewer, *Assessment for Effective Intervention.* September 2014 – Present
Assistant Reviewer, *School Psychology Quarterly*. December 2013 – Present

## HONORS AND AWARDS

Counseling, Clinical, and School Psychology Travel Grant, University of California, Santa Barbara January 2017
Counseling, Clinical, and School Psychology Research Fellowship, University of California, Santa Barbara June 2016
Center for School Based Youth Development Research Award, University of California Santa Barbara June 2016

Graduate Student Association Travel Grant, University of California, Santa Barbara — February 2016

Counseling, Clinical, and School Psychology Travel Grant, University of California, Santa Barbara — February 2016

Graduate Student Association Travel Grant, University of California, Santa Barbara — February 2015

Counseling, Clinical, and School Psychology Travel Grant, University of California, Santa Barbara — February 2015

Counseling, Clinical, and School Psychology Research Grant, University of California, Santa Barbara — June 2014

Graduate Suma Cum Laude, University of California, Los Angeles — June 2013

The Dissemination and Implementation Science SIG Presentation Award — 2012
"How much is enough? Identifying clinically-relevant information for decision-making models"

## PROFESSIONAL AFFILIATIONS

American Psychological Association; Division 16, School Psychology
National Association of School Psychologists
California Association of School Psychologists
Central Coast Association of School Psychologists
Ventura County Association of School Psychologists

ABSTRACT

A Longitudinal Investigation of Dual-Factor Mental Health in Adolescence

by

Stephanie Anne Moore

As supporting youths' mental health increasingly becomes a priority for school-based professionals, methods for identifying youth who may benefit from additional mental health supports are needed. Mental health has traditionally been defined from a deficit-based perspective, wherein mental health was assumed if youth were not experiencing psychopathology. Contemporary scholarship, however, increasingly asserts that the absence of mental illness is insufficient for mental health. Dual-factor models describe mental health as consisting of two separate yet interrelated constructs of well-being and psychopathology. Research using a dual-factor approach to examine youths' mental health has most often used rationally determined cut points to define mental health groups differing along each of the well-being and psychopathology dimensions. In two studies, a dual-factor approach to mental health in adolescents was investigated. In Study 1, an alternate approach to classification, latent profile analysis (LPA), was used to empirically identify mental health subtypes of high school students as well as to examine the relation of mental health profiles identified in Grades 9 through 11 with Grade 12 indicators of academic and social-emotional well-being. Results yielded four mental health subtypes: *complete mental health*, *moderately mentally*

*healthy*, *symptomatic but content*, and *troubled*. Students with profiles characteristic of higher levels of well-being and lower levels of distress reported higher grades, prosocial contribution to community, and life satisfaction, and less frequent symptoms of anxiety and depression, illustrating the validity of the LPA approach. In Study 2, the longitudinal stability of empirically-identified dual-factor mental health profiles was examined across Grades 9 to 12 using two cohorts of students. Similar to Study 1, LPA was used to empirically identify mental health profiles. Latent transition analysis (LTA) was then used to examine the stability of emerging profiles over the four academic years. An LTA model assuming full measurement invariance, non-stationary transitions, and controlling for cohort indicated that the *complete mental health* profile exhibited the greatest average stability followed by *moderately mentally healthy* and *symptomatic but content* profiles. The *troubled* profile exhibited the least stability. Taken together, the findings from both studies support further investigation of methods used to classify students mental health in school settings as well as regular monitoring of students' dual-factor mental health (e.g., through universal screening) so as to accurately inform mental health promotion, prevention, and intervention efforts.
*Keywords:* dual-factor mental health, adolescent, classification, stability, latent profile analysis (LPA), latent transition analysis (LTA).

TABLE OF CONTENTS

A Longitudinal Investigation of Dual-Factor Mental Health in Adolescence

## Introduction

Supporting mental health within school settings has become a priority for many practitioners, scholars, and educational stakeholders (e.g., Brock, 2015). Increasingly, policies and mandates at national, state, and local levels are supporting the movement to address mental illness and promote the mental health of youth in schools. For example, the recent reauthorization of the Elementary and Secondary Education Act, the Every Student Succeeds Act (ESSA; December 2015), provides additional funding streams for states to create safe and supportive learning environments for all students, including efforts to implement school-based mental health programs and comprehensive mental health supports (Strobach, 2015). Concurrently, professional organizations are encouraging practitioners, scholars, and trainees to attend to the mental health needs of students. For example, the National Association of School Psychologists (NASP) advocates for efforts to meet the mental health needs of youth within both their practice model (2010a) and standards for professional training (2010b).

This increased focus on mental health promotion stems from the growing evidence that mental health is linked to a variety of later outcomes, including school performance, academic achievement, and school attendance (e.g., Boyce et al., 2002; Bradley, Doolittle, & Bartolotta, 2008; DeSocio & Hootman, 2004; Suldo, Thalji, & Ferron, 2011; Roderick et al., 1997), yet a disproportionate percentage of students receive needed mental health care (e.g., Kataoka, Zhang, & Wells, 2002). However, the majority of youth who do receive mental health supports are served within a school setting (Rones & Hoagwood, 2000), with schools being a common entry point into mental health services (Brock 2015; Farmer, Burns, Phillips, Angold, & Costello, 2003). As such, mental health promotion and mental illness identification, prevention, and intervention are growing priorities not only for preventing deleterious school and life outcomes (Brock, 2015), but also for promoting youths' thriving (Furlong, Dowdy, Carnazzo, Bovery, & Kim, 2014).

Concurrent with increasing recommendations to support the mental health of youth, the way in which mental health is defined has expanded. Mental health has historically been defined in relation to mental illness or psychopathology, such that an individual was considered to be mentally healthy if they were not mentally ill. This conceptualization of mental health and illness assumes a single, bipolar mental health continuum, with illness/psychopathology lying on one end and health/well-being lying on the other (Keyes, 2005). Congruent with this perspective, much of school psychological work has been deficit- or problem-focused. For example, when addressing the mental health needs of adolescents, schools largely operate under a refer-test-place model of service delivery whereby struggling students are referred to the school psychologist to assess their need for specialized education or related services (Cash & Nealis, 2004). However, this approach results in an inefficient use of school resources that get limited primarily for use in assessment and service provision for a small, high risk group of students (Kleiver & Cash, 2005).

Arising from dissatisfaction with deficit-based approaches, definitions of mental health during the positive psychology movement shifted to include an explicit focus on the presence of positive health indicators (e.g., well-being [e.g., Seligman, 2002] or social-emotional assets/strengths [e.g., Scales, 1999]), such that the whole student population can be supported though efforts to nurture strengths, to promote thriving, and to foster well-being. Thus, contemporary mental health researchers increasingly recommend conceptualizing mental health more broadly, such that mental health is understood as (a) being distinct from mental illness and (b) including indicators of well-being (e.g., Seligman & Csikszentmihalyi, 2000).

## Dual-Factor Mental Health

Contemporary “dual-factor” (Suldo & Shaffer, 2008) or “two-continua” (Westerhof & Keyes, 2010) models of mental health that integrate a consideration of both psychopathology and well-being into conceptualizations of mental health and mental illness have emerged as an alternative to traditional illness-focused conceptualizations. For the purpose of the current dissertation, the term “dual-factor” will be used to refer to models that explicate mental health as composed of two separate, yet related constructs: (a) indicators of psychological risk, distress, or psychopathology (i.e., negative indicators of mental health), and (b) indicators of social-emotional strength or subjective well-being (i.e., positive indicators of mental health). Contrary to the bipolar view of mental health, dual-factor frameworks propose that mental health and mental illness comprise separate continua, with levels of both health and psychopathology varying within a given individual (Antaramian, Huebner, Hills, & Valois, 2010). Dual-factor models, therefore, propose an expanded conceptualization of mental health functioning.

The dual-factor model defines the two mental health groups that are congruent with the traditional approach: (a) youth who exhibit high psychopathology/distress concurrent with low well-being, and (b) youth who exhibit low psychopathology/distress and high well-being (Greenspoon & Saklofske, 2001). Additionally, groups of students previously unable to be identified, such as youth who are concurrently experiencing high levels of psychopathology and well-being or who are experiencing low levels of both psychopathology and well-being, are defined within a dual-factor approach. Therefore, moving beyond a deficit-based model, a comprehensive, dual-factor mental health approach allows school stakeholders to support the entirety of a student body through a range of interventions designed to reduce distress in addition to those designed to promote well-being (Suldo & Shaffer, 2008).

Support for a dual-factor model of mental health has been found among children (e.g., Greenspoon & Saklofske, 2001), adolescents in middle (e.g., Antaramian et al., 2010; Suldo & Shaffer, 2008) and high school (Suldo, Thalji-Raitano, Kiefer, & Ferron, 2016), and adults (e.g., Renshaw & Cohen, 2014). Most often, four mental health groups have been defined using dichotomous criteria informed by rationally determined cut-points (Kim, Dowdy, Furlong, & You, 2016). The four groups include: complete mental health (high well-being, low distress), troubled (low well-being, high distress), symptomatic but content (high well-being, high distress), and vulnerable (low well-being, low-distress; Antaramian et al., 2010; Greenspoon & Saklofske, 2001; Lyons, Huebner, Hills & Shinkareva, 2012; Renshaw & Cohen, 2014; Suldo & Shaffer, 2008; Thalji, 2013; Venning, Wilson, Kettler, & Eliott, 2013). This previous work has supported differences among mental health groups with respect to key outcomes, including academic achievement (Suldo & Shaffer, 2008), engagement (Antaramian, Huebner, Hills, & Valois, 2010), and physical health (Renshaw & Cohen, 2014). Individuals with complete mental health have been found to experience the most positive outcomes across domains.

The criteria used to form mental health groups, however, have varied across empirical investigations and practical applications. For example, some research used established decision points for norm-referenced measures (e.g., *T* scores of 60 are often used to indicate elevated risk or problems on behavior measures), whereas others used logically determined values based upon students' raw scores, sample means, or standardized scores (Greenspoon & Saklofske, 2001; Kim et al., 2016; Suldo & Shaffer, 2008). Moreover, whereas much research has defined the four groups described above, others have defined up to nine unique mental health groups (e.g., Furlong, Dowdy, Carnazzo, Bovery, & Kim, 2014). Application of the dual-factor classification of mental health is currently limited by the inconsistent classification criteria that are used and recommended across studies using a cut-point approach. Given the varied criteria, consistency in classification into a given mental health group across methods is unattainable.

In addition, although the empirical literature substantiating the dual-factor approach and the relation between dual-factor mental health group membership and various outcomes has grown, current research is limited by its cross-sectional nature. Few studies have investigated the longitudinal stability of dual-factor mental health in youth, with previous research examining patterns in stability and change in mental health group membership in early elementary school (Compton, 2016), middle school (Kelly, Hills, Huebner, & McQuillin, 2012), and high school (McMahan, 2012) over no more than a one-year period. Across studies, the complete mental health group demonstrated the greatest stability followed by the troubled group. Either the symptomatic but content (McMahan, 2012) or vulnerable (Compton, 2016; Kelly et al., 2012) groups were found to exhibit the least stability. However, understanding stability of dual-factor mental health is important in informing the full range of school-based mental health services, including health promotion, prevention, early intervention, and treatment.

## Dissertation Purpose

The purpose of this dissertation is to examine dual-factor mental health among adolescent high school students. This dissertation was organized around two studies investigating (a) an alternative approach to dual-factor mental health classification and (b) the longitudinal stability of dual-factor mental health across the high school years. A brief description of each study is included below. Then, formatted in two individual manuscripts, the empirical background and rationale, method, results, and discussion are presented for each study. A general discussion, integrating conclusions from the two studies is presented last.

The discrepancies in dual-factor mental health classification observed in previous research highlight one of several limitations to cut-score classification approaches (e.g., Nylund, Bellmore, Nisina, & Graham, 2007). For example, given varied criteria, inconsistencies in group membership are likely to arise depending upon the criteria used. In addition, dichotomous classification schemes can oversimplify heterogeneity among defined groups. Thus, investigations into alternative classification approaches are recommended (Kim et al., 2016; Rebelez-Ernst, 2015). Initial research has been conducted to examine the utility of an empirical approach to mental health classification using latent profile analysis (LPA) to identify (rather than define) emerging mental health groups based upon students' responses to indicators of well-being and distress (Kim et al., 2016; Rebelez-Ernst, 2015). However, each investigation examined LPA models for well-being and distress separately. Cross-tabulating emerging classes resulted in at least 15 discrete mental health groups, with many groups comprising less than 5% of the study's sample. Additional research is needed to further investigate an empirical approach to dual-factor mental health classification using parsimonious models. Therefore, the goal of Study 1 was to explore a LPA approach to classifying dual-factor mental health. In particular, Study 1 examined the structural stability of emerging LPA identified mental health groups over three years of high school as well as the relation of the empirically identified groups to individual demographic characteristics and later social-emotional and academic outcomes.

Expanding upon Study 1, Study 2 investigated the longitudinal stability of empirically-identified dual-factor mental health groups across the high school years. Although the literature examining the stability of psychopathology and well-being is relatively well-defined, supporting moderate stability for each construct when examined independently (e.g., Deković, Buist, & Reitz, 2004; Huebner, 2004), research describing patterns in stability of dual-factor mental health is limited. Study 2 used latent transition analysis (LTA), a longitudinal extension of LPA, to explore stability of emerging empirically-identified mental health groups over a four year period. Patterns in latent class membership were examined across Grades 9 to 12 and probabilities of transitioning between mental health groups were explored for one- (e.g., Grade 9 to 10, Grade 10 to 11, Grade 11 to 12) and two-year (e.g., Grade 9 to 11, Grade 10 to 12) intervals. Specifically, Study 2 investigated which dual-factor mental health groups exhibited the greatest stability across Grades 9 through 12, if patterns in stability (i.e., likelihood of transition) were the same across transition points, and whether effects of dual-factor mental health group membership persist to affect group membership two years later. Together, the results of these two studies can contribute to the growing understanding of dual-factor mental health as well as inform mental health assessment and intervention efforts to support students’ mental health needs in schools.

**Study 1:**

**An Empirical Approach to Complete Mental Health Classification in Adolescents**

## Abstract

Dual-factor models of mental health including a focus on well-being and distress are increasingly supported. The current study utilized latent profile analysis (LPA) to empirically identify subtypes of dual-factor mental health during high school and to examine the relation of mental health groups to distal indicators of academic performance, well-being, and psychopathology. A sample of 332 adolescent high school students reported on their social-emotional strengths and psychological distress during the Fall of their ninth-, tenth-, and eleventh-grade years. In twelfth grade, students reported on outcome measures assessing their academic and social-emotional experiences. Independent LPAs for each grade year yielded four mental health subtypes: *complete mental health*, *moderately mentally healthy*, *symptomatic but content*, and *troubled*. Across high school years, most students belonged to the complete or moderate mental health classes, with the troubled class consistently representing the smallest proportion of the sample. Students in classes with higher levels of strengths and lower levels of distress reported higher grades, prosocial contribution to community, and life satisfaction, and less frequent symptoms of anxiety and depression, illustrating the validity of the LPA approach. Implications and future direction for research and school-based practice are discussed.

*Keywords*: dual-factor mental health, two-continua mental health, adolescents, classification, latent profile analysis (LPA)

**An Empirical Approach to Complete Mental Health Classification of Adolescents**

As supporting youths' mental health increasingly becomes a priority for school-based professionals (e.g., Brock, 2015), methods for identifying youth who may benefit from additional mental health supports and services are needed. As a first step in prevention and early intervention efforts, universal mental health screening has been recommended as one approach to identifying the broader mental health needs of youth within school settings (e.g., Glover & Albers, 2007; Kamphaus, Reynolds, & Dever, 2014). Concurrently, conceptualizations of mental health have been expanding from traditional, illness-focused models toward dual-factor (e.g., Greenspoon & Saklofske, 2001; Suldo & Shaffer, 2008) or two-continua (e.g., Westerhof & Keyes, 2010) models of mental health that promote a focus on both psychological distress and social-emotional well-being as separate, yet related dimensions of mental health. Thus, a contemporary approach to universal screening, screening for students' strengths in addition to distress or psychopathology, what has been termed *complete mental health screening* (Furlong, Dowdy, Carnazzo, Bovery, & Kim, 2014), has been proposed as one method to provide schools with a comprehensive picture of youths' mental health functioning. Students' complete mental health screening data are then used to inform their classification into mental health groups that guide intervention planning and implementation.

The empirical literature substantiating a dual-factor model of mental health has most often relied on predetermined decision points when forming mental health groups that vary along indicators of distress and well-being (Kim, Dowdy, Furlong, & You, 2016). This classification scheme results in four groups differentiated by levels of distress and well-being, which have been found to differentially predict important outcomes including academic achievement (Suldo & Shaffer, 2008), engagement (Antaramian, Huebner, Hills, & Valois, 2010), and physical health (Renshaw & Cohen, 2014). However, limitations associated with the use of rational cut-score approaches to classification based on varied criteria used to form mental health groups in dual-factor studies call for the exploration of other approaches to mental health group classification, such as person-centered, empirically-based classification (Kim et al., 2016). Although initial research has been conducted to investigate the utility of empirically defined mental health groups formed using indicators of well-being and distress (Kim et al., 2016; Rebelez-Ernst, 2015), additional research is needed that examines parsimonious models of empirically defined dual-factor mental health that can inform early identification and intervention efforts. The aims of the current study are to: (a) explore an empirically based, latent class approach to dual-factor mental health classification; (b) investigate the structural stability of emerging groups over three years; and (c) examine the relation of the empirically derived mental health groups to individual demographic characteristics and later academic and social-emotional outcomes.

## Defining Complete Mental Health

Although psychopathology has been at the forefront of psychology research and practice, including within school settings, mental health is increasingly recognized as more than the absence of mental illness (e.g., World Health Organization, 2016). Contemporary dual-factor (Suldo & Shaffer, 2008) or two-continua (Westerhof & Keyes, 2010) models of mental health that integrate degree of both psychopathology and well-being into conceptualizations of mental health and mental illness have emerged as an alternative to bipolar models (i.e., health and illness lying on a single continuum with health indicating the absence of illness; Greenspoon & Saklofske, 2001). Dual-factor models of mental health explicate mental health as composed of two separate, yet related constructs: (a) psychological distress or psychopathology (i.e., negative indicators of mental health), and (b) social-emotional strengths or subjective well-being (i.e., positive indicators of mental health). Dual-factor frameworks propose that mental health and mental illness comprise separate continua, with levels of both well-being and distress varying within an individual (Antaramian et al., 2010).

Conceptualizing mental health from a dual-factor perspective provides a holistic description of mental health functioning among adolescents. Whereas two groups of students are identified using a bipolar view of mental health, including (a) youth who exhibit high distress concurrent with low well-being and (b) youth who exhibit low distress and high well-being (Greenspoon & Saklofske, 2001), the binary classification procedures used within a dual-factor conceptualization of mental health logically produce additional mental health groups. For example, individuals (c) who are concurrently experiencing high levels of psychopathology and strengths or (d) who are experiencing low levels of both psychopathology and strengths are identified. Therefore, in addition to identifying students who are experiencing significant psychological distress, dual-factor models also identify students who do not display significant psychopathology, but who have suboptimal positive mental health (Antaramian et al., 2010). The term, “complete mental health,” serves to emphasize mental health as determined by both well-being and psychological distress, with youth who are described to have complete mental health having high levels of well-being in addition to low levels of distress (Moore et al., 2015).

Dual-factor, complete mental health models have been supported for use with children (e.g., Greenspoon & Saklofske, 2001), adolescents in middle (e.g., Antaramian et al., 2010; Suldo & Shaffer, 2008) and high school (Suldo, Thalji-Raitano, Kiefer, & Ferron, 2016), and adults (e.g., Renshaw & Cohen, 2014). Although the tools used to define complete mental health and the constructs of well-being and distress have varied across empirical investigations, similar trends have emerged in the relation of dual-factor mental health groups to outcomes of interest. For example, in measuring well-being, some scholars have utilized measures of subjective well-being (defined by positive affect, negative affect, and life satisfaction; Antaramian et al., 2010) whereas others have relied upon measures of social-emotional strengths found to be predictive of subjective well-being (e.g., Dowdy et al., 2015; Kim, Furlong, Dowdy & Felix, 2014). Similarly, psychopathology has been measured using comprehensive assessment tools that provide information about the clinical significance of internalizing and externalizing symptoms (e.g., Suldo & Shaffer, 2008; Suldo et al., 2016) as well as with briefer screening instruments that provide information about an individual’s level of psychological distress or behavioral and emotional risk (e.g., Dowdy et al., 2015; Kim et al., 2014, 2016). However, across investigations, individuals with complete mental health (i.e., higher levels of positive psychological traits and lower levels of psychological distress) are found to have more positive developmental indicators. For example, among adolescents, individuals with complete mental health have been found to have superior engagement (Antaramian et al., 2010; Lyons, Huebner, & Hills, 2013), academic achievement (i.e., grade point average; Antaramian et al., 2010; Lyons et al., 2013), school attendance (Suldo & Shaffer, 2008), social relationships and functioning (Suldo & Shaffer, 2008; Suldo et al., 2016), physical health (Suldo & Shaffer, 2010; Suldo et al., 2016), and identity development (i.e., self-concept, self-esteem, meaningful involvement in activities; Suldo et al., 2016). Moreover, among youth who experience distress, the presence of well-being has been indicated to have a buffering effect on individuals' outcomes, including for social support and peer victimization, engagement, academic-self perceptions, identity development, and physical health (Lyons et al., 2013; Suldo & Shaffer, 2008; Suldo et al., 2016). The growing research on dual-factor mental health, including investigations revealing differential functioning based upon mental health group membership, supports the use of an expanded conceptualization of mental health consisting of both well-being and distress. However, the criteria used to form dual-factor mental health groups vary across empirical investigations and practical applications, which is problematic given that the defined mental health groups are characteristic of the cut-points used to determine group membership. These cut-points are selected by the researchers and then applied to describe the population's mental health characteristics. Inconsistencies in classification and a priori selection criteria indicate that the defined groups may not accurately capture youth's mental health experiences. Thus, a primary goal of the present study was to explore a person-centered, empirical classification approach that allows groups to emerge based upon similarities among members within a population, rather than using pre-determined characteristics to defined groups. The empirical approach lends itself to cross-study standardization (Masyn, 2013) and can refine the understanding of the characteristics of adolescent dual-factor mental health groups (Nylund, Bellmore, Nishina, & Graham, 2007).

## Classification of Complete Mental Health

The majority of research on dual-factor mental health has classified youth based upon a rationally formed dichotomous categorization scheme for each of the well-being and distress dimensions of mental health (e.g., Kim et al., 2016). That is, cut points are specified to distinguish youth who experience high versus low levels of well-being and distress. Using the dichotomous cut score approach to classification, four mental health groups are always formed across investigations (Antaramian et al., 2010; Greenspoon & Saklofske, 2001; Lyons et al., 2012; Renshaw & Cohen, 2014; Suldo & Shaffer, 2008; Thalji, 2013; Venning, Wilson, Kettler, & Eliott, 2013) and include groups of students with (a) high well-being and low distress (e.g., complete mental health), (b) high well-being and high distress (e.g., symptomatic but content), (c) low well-being and low distress (e.g., vulnerable or languishing), and (d) low well-being and high distress (e.g., troubled). A variety of criteria have been used for categorization based upon differing cut points. For example, some research used established decision points for norm-referenced measures (e.g., *T*-scores of 60 are often used to indicate elevated risk or problems on behavior measures) whereas others used values based upon students' raw scores, sample means, or standardized scores (Kim et al., 2016). For example, with elementary aged children, Greenspoon and Saklofske (2001) used published norms for the *Behavioral Assessment System for Children-Second Edition* (BASC-2; Kamphaus & Reynolds, 2007) when dichotomizing psychopathology and *T*-score local norms for their well-being criterion, the *Multidimentional Life Satisfaction Scale* (MSLSS; Huebner, 1994). Others have used predetermined criteria in selecting raw- or mean-score cut points (e.g., such that 30% of the sample is classified as having low well-being; e.g., Antaramian et al., 2010; Suldo & Shaffer, 2008). Assigning youth to either high or low well-being and high or low distress categories forms the four mental health groups specified above.

Although the cut score approach forms unique mental health groups, the resulting membership in the four groups is just one of many possible group assignments that are dependent upon the number of cut points selected and the criteria used. An inherent disadvantage to this approach to classification is that most often there are not clear criteria regarding where to designate cut points or if four groups is optimal (e.g., Nylund et al., 2007b). Even though the majority of the dual-factor research has examined the properties of four groups, additional cut points could be specified to generate a greater number of groups that describe more of the variability in youths' mental health experiences. For example, rather than dichotomizing well-being and distress, Furlong, Dowdy, and colleagues (2014) used standardized *z*-scores to classify students into one of four strength groups indicative of well-being (i.e., *low*, *below average*, *above average*, and *high strengths*) and *T*-scores to form three distress groups (i.e., *normal*, *elevated*, *very elevated*). Via this design, 12 mental health groups were formed when students' strength and distress classifications were merged. After examining the number of students falling into each group, the authors combined similar groups with few individuals to result in a final total of nine mental health groups. Thus, additional variation in youths' mental health is evident when additional cut points are added. Nevertheless, classification via the cut score approach can be insensitive to the degree of variation in mental health among youth (Kim et al., 2016). For example, when dichotomous classification criteria are specified such that youth scoring above the 30$^{th}$ percentile on a well-being measured are indicated to have high well-being, individuals exhibiting moderate levels of well-being (e.g., in the 40$^{th}$ percentile) are regarded as having similar levels of well-being as those individuals with the highest levels of well-being (e.g., in the 90$^{th}$ percentile; Kim et al., 2016). As such, the mental health groups formed that, in reality, exhibit much heterogeneity are treated as homogenous and the complexity of students' mental health experiences is not adequately captured. Thus, the cut-score approach to categorization can over-simplify complexity in profiles of youths' mental health.

Additionally, when inconsistent and sample-dependent criteria are recommended across studies, as has been seen in dual-factor research, an individual may be classified into one mental health group when one set of criteria are used, but into a different group when another set of criteria are used. Thus, replication of results across studies is impossible. For example, considering the four consistently identified complete mental health groups, the majority of adolescents have been found to experience complete mental health [42% (Venning et al., 2013) to 64% (Lyons et al., 2012)], followed by symptomatic but content [9% (Lyons et al., 2012) to 36% (Venning et al., 2013)], troubled [8% (Antaramian et al., 2010) to 20% (Lyons et al., 2012)], and languishing [5% (Venning et al., 2013) to 13% (Suldo & Shaffer, 2008)]. The observed differences in the proportion of youth who are classified into each mental health group within each study's sample may be impacted by sample-specific characteristics, but are also indicative of disparities in classification that are observed when criteria used to classify individuals' mental health varies across investigations. A person-centered, empirical approach to classification that identifies groups (i.e., latent classes or profiles) based upon individual observed response pattern provides another approach for identifying emerging groups (Nylund et al., 2007b).

**Latent Profile Analysis: A Person-Centered Approach to Classification**

Latent profile analysis (LPA) is a person-centered, empirical approach to classifying the heterogeneity within groups of people (e.g., Masyn, 2013; Vermunt, 2004). As a person-centered approach, LPA identifies differences and similarities among individuals with respect to how variables measuring constructs of interest are related to each other. When applied, LPA is performed in an exploratory manner and assumes that the underlying population is heterogeneous but also that the population consists of a finite number of meaningful, more homogenous groups (Laursen & Hoff, 2006; Masyn, 2013). A categorical latent variable, indicative of group membership, is specified to identify unobserved (latent) groups (also called classes or profiles) based upon similarities in their response patterns across indicators. Through a model building process wherein numerous models specify increasingly more classes, statistical criteria are used to evaluate the resulting models and to decide on the number of latent groups, also called classes or profiles. Rather than predetermining the number of groups to be formed using logical cut points, LPA allows for meaningful classes to be empirically identified, and then to be evaluated for accuracy and validity. Thus, when well-being and distress are examined concurrently, LPA classification allows for groups to emerge that may differ in both dimension (i.e., presence of well-being but absence of distress) and relative severity (i.e., varying levels of well-being and/or distress) of mental health.

Two previous studies (Kim et al., 2016; Rebelez-Ernst, 2015) have examined dual-factor mental health using an LPA approach to classification. In each study, separate latent class models were specified for social-emotional strengths and psychological distress, with classes from the best-fitting strength and distress models being cross-tabulated to form complete mental health groups. Kim and colleagues (2016) identified five profiles of strengths (i.e., *low*, *below average*, *average*, *above average*, and *high*) and three profiles of distress (i.e., *elevated internalizing only*, *both internalizing and externalizing*, and *low distress*) whereas Rebelez-Ernst (2015) identified four profiles of strengths (i.e., *very low*, *below average*, *average*, and *above average*) and four profiles of distress (i.e., *no* *psychosocial distress*, *internalizing*, *externalizing*, and *externalizing and internalizing combined*). When the emerging strength and distress profiles were cross-tabulated, Kim et al. (2016) and Rebelez-Ernst (2015) identified 15 and 16 complete mental health groups, respectively. However, when examining the proportion of students in each of these samples in each emerging mental health group, many of the emerging groups described fewer than 5% of the study's participants, calling into question the practicality of each group for informing prevention or intervention efforts. In addition, although these previous LPA investigations examined both positive and negative indicators of mental health using a dual-factor approach, adolescents' characteristics on each element of mental health were considered separately and then cross-tabulated, as has been done with the traditional cut score classification approach, when forming the final mental health groups. Additional research examining parsimonious approaches to LPA classification that specify models that examine emerging groups when well-being and distress are examined simultaneously is needed to better inform use of mental health data to identify youths' mental health and, then, to inform intervention. Moreover, research investigating whether the number of emerging mental health groups is consistent over time (i.e., structural stability) is needed.

## Predictors and Outcomes of Adolescents' Mental Health

Given the limited research investigating empirically defined dual-factor mental health groups, the current study examined demographic predictors of adolescents' complete mental health group membership as well as the relation of group membership to later academic and social-emotional outcomes. In particular, the relation between empirically defined mental health groups on adolescents' outcomes between one to three years later were examined in the current study as a first step in examining the viability of using empirically defined groups and in understanding their predictive utility.

**Demographic Indicators of Mental Health Group Membership**

The link between gender and psychopathology has been well-established (e.g., Merikangas et al., 2010). By adolescence, females are significantly more likely than males to experience internalizing problems (Galambos, Leadbeater, & Barker, 2010; Hale, Raaijmakers, Muris, van Hoof, & Meeus, 2008), whereas males are more likely to experience symptoms of externalizing problems (Meirkangas et al., 2009). Similarly, in previous empirical investigations into complete mental health, females were more likely to be classified into a mental health class characteristic of high internalizing symptoms than were male students (Rebelez-Ernst, 2015). However, researchers have concluded that gender has a negligible impact on subjective well-being (Lent, 2004).

With regards to ethnicity, research findings are inconsistent (i.e., Merikangas, Nakamura, & Kessler, 2009). Some research has suggested that African American youth experience lower rates of depressive symptoms when compared to White (Angold et al., 2002) or Latinx youth (e.g., Roberts, Roberts, & Chen, 1997), and that Latinx youth, particularly Mexican-Americans, experience greater rates of depressive symptoms compared to their White and African American peers (e.g., Roberts & Chen, 1995). A majority of studies investigating well-being have not found differences between youth of varied racial and ethnic backgrounds (e.g., Gilman & Huebner, 2003; Lent, 2004). Similarly, in an investigation of empirically defined dual-factor mental health, no systematic differences in likelihood of class membership were evident based upon an individuals' ethnic identity (Rebelez-Ernst, 2015). The present study sought to further examine the indicators of adolescent gender and ethnicity to determine their relations with dual-factor mental health profiles.

## Predictive Validity of Dual-Factor Mental Health Class

Within prevention and early intervention frameworks, the ability of measurement and classification schemes to predict later functioning is foundational in guiding applied work. Understanding the relation between group membership and desired and undesired outcomes is needed in order for formed groups to be informative in guiding intervention. Thus, as part of the initial validation efforts of the current study, we sought to investigate the relation between complete mental health, characterized by both well-being and distress, with the distal outcomes of academic achievement as well as positive (i.e., prosocial contribution to community, life satisfaction) and negative (i.e., symptoms of depression and anxiety) indicators of later psychological functioning.

**Academic achievement.** The relation between mental health and academic achievement is widely documented when well-being and distress indicators are examined independently with research supporting differences in course grades, standardized test scores, engagement, attendance, risk of drop out, and college enrollment based upon one's positive and negative mental health status (e.g., Duchesne, Vitaro, Larose, & Tremblay, 2008; Frazier, Youngstrom, Clutting, & Watkins, 2007; Gilman & Huebner, 2006; Masten et al., 2005; Reschly, Huebner, Appleton, & Antaramian, 2008; Suldo et al., 2011). Using the dual-factor framework, grades, attendance, engagement, and academic self-perceptions have been found to vary according to youths' subjective well-being and psychopathology, with individuals exhibiting complete mental health experiencing the most positive academic outcomes and those in the troubled and vulnerable groups experiencing the poorest academic outcomes (Antaramian et al., 2010; Suldo & Shaffer, 2008; Suldo, Thalji, & Ferron, 2011).

**Prosocial contribution to community.** Similar to concepts like civic engagement (Adler & Goggin, 2005) and prosocial purpose (Radke-Yarrow, Zahn-Waxler, & Chapman, 1983), individual characteristics associated with prosocial contribution (i.e., youths' engagement and giving to self, others, and community) are key components in healthy development (Scales & Benson, 2005). For example, participation in meaningful activities contributes to adolescents' developing identities and has been found to be related to their mental health and life satisfaction (LaGuardia & Ryan, 2002; Maton, 1990). Thus, prosocial contribution to others, community, and society is considered an important area of psychological competence to be developed in adolescence. In a recent study examining the dual-factor mental health model with high school students, Suldo and colleagues (2016) investigated the relation between complete mental health and participation in meaningful activities (i.e., skill utilization, social contribution, and goal attainment related to an activity of positive personal significance to participants). Results indicated an additive effect, such that youth with higher levels of well-being (i.e., complete mental health or symptomatic but content) reported greater involvement with meaningful activities (Suldo et al., 2016). The current study aims to expand upon these findings by examining the relations between dual-factor mental health and youths' contribution to their community as an indicator of their thriving development.

**Life satisfaction.** Life satisfaction (i.e., an individuals' "overall appraisal of the quality of his or her life;" Gilman & Huebner, 2003; p. 193) is regarded as an important indicator of youths' positive psychological functioning and is a key component in subjective well-being. For example, one's degree of life satisfaction has been related to later onset of depression, quality of interpersonal relationships, school dropout, self-esteem, and locus of control (e.g., Furr & Funder, 1998; Gilman & Huebner, 2003; Lewinsohn, Redner, & Seeley, 1991). In research utilizing social-emotional strengths as the indicator of well-being, individual's strengths are strongly correlated with subjective well-being ($r$ = .57) and account for a significant proportion of the variance in subjective well-being (Kim et al., 2014). Moreover, individual character strengths, such as zest, gratitude, and hope, are significantly associated with life satisfaction (Park, Peterson, & Seligman, 2004). In a study examining the relation of empirically identified dual-factor mental health groups formed via social-emotional strengths with life satisfaction, youth reporting higher levels of strengths also reported greater satisfaction with life, across levels of distress (Kim et al., 2016). As the focus of the current study is also on mental health groups formed via social-emotional strengths, we aimed to extend Kim and colleagues' (2016) findings with a unique sample of adolescents classified into empirically identified mental health groups.

**Symptoms of psychopathology.** Longitudinal research has demonstrated that early experiences of well-being or distress are predictive of later mental health (e.g., Deković, Buist, & Reitz, 2004; Huebner, Funk, & Gilman, 2000). Youth who report mental health challenges or limited social-emotional competence are more likely to go on to experience negative mental health, academic, and social outcomes in late adolescence or adulthood (e.g., Deković et al., 2004; Ferdinand, Verhulst, & Wiznitzer,1995; Obradović, Burt, & Masten, 2010; Rapee, Schniering, & Hudosn, 2009). Similarly, youths' experiences of well-being (including satisfaction, strengths, and assets) are related over time (e.g., Huebner, 2004; Obradović, van Dulmen, Yates, Carlson, & Egeland, 2006; Scales, Benson, Roehlkepartain, Sesma, & Van Dulmen, 2006). However, research is needed that examines the intersection of the two factors of mental health functioning on later adverse outcomes. Given the increasing relevance of prevention and early intervention efforts within school systems (e.g., Glover & Albers, 2007), understanding the relation between dual-factor mental health and later experiences of distress is crucial in utilizing complete mental health group membership to inform school-based intervention for youth with varied mental health profiles. Thus, the current study aims to examine the relation between dual-factor mental health group membership across three years of high school with Grade 12 depression and anxiety symptoms as an initial step in validating the emerging mental health groups.

## The Present Study

This study used LPA to empirically define complete mental health groups, as assessed via universal screening data, with adolescents in Grades 9, 10, and 11. Across three years, adolescents reported on their social-emotional strengths and psychological distress. LPA analyses performed for students in each of Grade 9, 10, and 11 were designed to examine whether patterns in dual-factor mental health were consistent at different points in high school, rather than to examine the stability of complete mental health of individual students' over time. Research first supporting structural stability of empirically defined complete mental health groups is required prior to examining the longitudinal stability of adolescents' complete mental health. To further understand the composition of emerging complete mental health profiles, the relation of gender and ethnicity with latent mental health group membership was also examined. Finally, the relation between adolescents' mental health class in each of Grades 9, 10, and 11 with Grade 12 academic and positive and negative social-emotional outcomes was explored. Thus, the goals of the present study were to (a) identify subtypes of dual-factor mental health using an empirically driven latent class approach to classification, (b) to examine the structural stability of dual-factor mental health classes at three different time points across three years of high school, and (c) to assess how empirically derived mental health class predicts grade 12 academic and social-emotional outcomes.

## Method

### Participants

Participants attended one high school in central California and included students who participated in a larger, ongoing universal complete mental health screening project occurring over four consecutive academic years. Target participants for the current study were students enrolled in Grade 9 during 2013-2014 who also completed the universal screening survey in Grade 12 (2016-2017), which included measures used as distal outcomes. Of the 497 students who completed the Grade 9 universal screening survey, 334 (67%) also had parent consent and student assent to complete the Grade 12 survey. Individuals who had at least three years of data across the four possible years when the survey was conducted were included in the analyses that are the focus of this study ($N$ = 332). Two students who completed only the Grade 9 and Grade 12 surveys were excluded from the current analyses. Using these criteria, the final sample for each year was: 332 (Grade 9), 324 (Grade 10), and 291 (Grade 11). Information obtained from students' archival school records in Grade 9 indicated that the participating sample was 48.5% female, 43.9% Latinx or Hispanic, 37.9% non-Hispanic White, 7.5% Asian or Pacific Islander, 1.2% African American, and 0.9% American Indian or Alaska Native. Race or ethnicity information was unavailable for 8.4%

of participants. In the current study, 47.3% of students were classified as socioeconomically disadvantaged and 8.4% were eligible to receive special education and related services.

**Procedures**

Data were collected as part of early identification and intervention efforts occurring through an ongoing partnership between researchers at one university and the participating high school. Each year, for four consecutive years, all students in Grades 9 through 12 were invited to participate in universal screening. During the first month of each academic year, following approval by the university's institutional review board, district approval, passive parental consent, and student assent, school personnel administered the screening surveys to participating students in a group format during one period of the regular school day. Administration scripts were provided to all classroom teachers to ensure fidelity of administration across classrooms each year.

Data were collected in the fall of 2013-2014 (Grade 9), 2014-2015 (Grade 10), 2015-2016 (Grade 11), and 2016-2017 (Grade 12). Students completed the screening survey, containing the measures used in the present study, electronically via an online survey (e.g., SurveyMonkey or Qualtrics) during Grades 9, 11, and 12. At the request of the school's administration, surveys were completed using paper-and-pencil format during Grade 10 data collection. Each year, within the two weeks following initial data collection, students who were absent on their class's initial screening day were provided with up to five additional opportunities to complete the survey. During the fall of Grade 9, 10, and 11, the well-being and distress measures to be used in the LPAs were administered. In order to examine the validity of students' emerging complete mental health class, five additional measures of academic or social-emotional outcomes were administered in the fall of Grade 12.

## Measures

### Dual-factor mental health measures.

***Social Emotional Health Survey-Secondary (SEHS-S).*** The 36-item SEHS-S assesses 12 positive psychological dispositions (e.g., self-efficacy, peer support, gratitude, and empathy), which load onto four second-order positive-mental-health domains and a third-order factor of covitality (Furlong, You, Renshaw, Smith, & O'Malley, 2014; You et al., 2014). The four positive-mental-health domains in the SEHS-S model are: *belief-in-self* (self-efficacy, self-awareness, persistence), *belief-in-others* (school support, peer support, family coherence), *emotional competence* (emotional regulation, empathy, self-control), and *engaged living* (optimism, gratitude, zest). Nine items, consisting of three items from each of three first-order psychological building blocks, comprise each of the four positive mental health domains. Students responded to statements related to their social-emotional functioning using an ordinal-response scale. On the gratitude and zest subscales, a 5-point response scale is used (1 = *not at all*, 2 = *very little*, 3 = *somewhat*, 4 = *quite a lot*, 5 = *extremely*). For each of the other 10 dispositions, adolescents indicate how true each statement is for them (1 = *not at all true of me*, 2 = *a little true of me*, 3 = *pretty much true of me*, 4 = *very much true of me*).

In the current study, mean scores for the four second-order positive psychological domains (*belief-in-self*, *belief-in-others*, *emotional competence*, *engaged living*) were computed and used as indicators of well-being for each year of data collection. One item on the *self-awareness* subscale of the *belief-in-self* domain (item 6, "I understand why I do what I do") was missing for all students on the 2015-2016 (Grade 11) survey. Given that the inter-item correlations of items within the *self-awareness* subscale on the SEHS-S ($r$ = .17 to .40) and the second-order *belief-in-self* domain ($r$ = .21 to .28; Renshaw, 2015) have been observed to fall within the recommended range (i.e., between .20 and .40; Allen & Yen, 2002; Piedmont, 2014), indicating reasonable homogeneity and unique variance, the mean item response for the *belief-in-self* domain for Grade 11 was computed without this missing item. Internal consistency reliability for each of the second-order psychological domains have been found to be adequate (e.g., *belief-in-self*, $\alpha$ = .76; *belief-in-others*, $\alpha$ = .81; *emotional competence*, $\alpha$ = .78; *engaged living*, $\alpha$ = .87; You et al., 2014). In the current study, Cronbach's $\alpha$ ranged from .76 (Grade 10) to .84 (Grade 11) for *belief-in-self*, .80 (Grade 9) to .87 (Grade 11) for *belief-in-others*, .78 (Grade 9) to .84 (Grade 11) for *emotional competence*, and .86 (Grade 9) to .91 (Grade 11) for *engaged living*.

***Strengths and Difficulties Questionnaire (SDQ).*** The SDQ is a 25-item self-report questionnaire designed to measure youths' behavior and feelings over the previous six months (Goodman, 1997, 1999). Students respond to each item using a three-point response scale (1 = *not true*, 2 = *somewhat true*, 3 = *certainly true*). A three-factor structure, including *emotional distress/withdrawal*, *behavioral reactivity/conduct problems*, and *prosocial behaviors/peer competence*, proposed by Dickey and Blumberg (2004) and Ruchkin et al. (2008), has been validated with U.S. youth and supports superior reliability estimates over the originally theorized five-factor SDQ model (Goodman, 1997, 1999). In the present study, consistent with recommendations for measurement efficiency in applied screening settings, the five highest loading items, supported in the Ruchkin et al. (2008) three-factor model, were used for each of the *emotional distress/withdrawal* (items 3, 6, 8, 13 and 16; $\lambda$ = .47 to .60) and the *behavioral reactivity/conduct problems* factors (items 2, 5, 10, 15, and 22; $\lambda$ = .56 to .62). The *emotional distress/withdrawal* items were used as a measure of internalizing distress (e.g., “I worry a lot”) while the *behavioral reactivity/conduct problems* items were used as a measure of externalizing distress (e.g., “I get very angry and often lose my temper”).

To examine the hypothesized two-factor structure of the 10 items used in the current study, an exploratory factor analysis (EFA) specifying one to three factors was performed using the total Grade 9 sample from 2013-2014 ($N$ = 497). Using criteria specified by Hu and Bentler (1999) and Browne and Cudeck (1989), a two-factor model comprised of *internalizing problems* and *externalizing problems* factors yielded the best empirical and substantive fit: Root Mean Square Error of Approximation (RMSEA) = .07, CI 90% [.05, .09], Comparative Fit Index (CFI) = .93, Tucker Lewis Index (TLI) = .89. However, one item hypothesized to measure externalizing distress (item 5, “I get angry and often lose my temper”) loaded poorly on the factor with externalizing items ($\lambda$ = .11) but strongly on the factor with internalizing items ($\lambda$ = .51). Therefore, this item was removed from the analysis. A final confirmatory factor analysis (CFA) model, specifying four items on the externalizing scale and five items on the internalizing scale yielded adequate fit: RMSEA = .08, CI 90% [.07, .10], CFI = .94; TLI = .92. In the current study, mean scores for the final five items from the *emotional/distress* and four items from *behavioral reactivity/conduct problems* were computed and used as indicators of internalizing and externalizing distress, respectively, for each year of data collection. Internal consistency reliability ($\alpha$) for the internalizing and externalizing composites in the current study ranged from .67 (Grade 9) to .75 (Grade 11), and .55 (Grade 9) to .67 (Grade 11), respectively.

**Demographic covariates.** Adolescents’ gender and ethnic identification data were collected via school archival records in Spring of 2013 (Grade 9). School records indicated students as male (0) or female (1). Given the low proportion of ethnicities aside from Latinx/Hispanic and non-Hispanic White in the current sample, ethnicity was dichotomized to include Latinx/Hispanic (1), comprising 52.1% of the sample, or non-Latinx/Hispanic (0).

**Academic performance.** Adolescents' academic performance was measured via one item from the California Healthy Kids Survey ("*During the past 12 months, how would you describe the grades you mostly received in school?*"; California Department of Education, n.d.). Using an eight-point response scale (1 = *mostly F's*, 2 = mostly *D's*, 3 = *C's and D's*, 4 = *mostly C's*, 5 = *B's and C's*, 6 = *mostly B's*, 7 = *A's and B's*, to 8 = *mostly A's*), students self-reported their academic performance over the previous year.

**Social-emotional outcomes.**

***Brief Multidimensional Students' Life Satisfaction Scale (BMSLSS).*** The BMLSS (Seligson, Huebner, & Valois, 2003) consists of five items designed to measure degree of life satisfaction for individuals aged 8 to 18 years. Respondents rate their degree of satisfaction in five general domains (i.e., friends, family, self, school, and living environment) that contribute to an overall life satisfaction score (Seligson et al., 2003). The five-item BMSLSS scores have demonstrated acceptable convergent validity with other well-established measures of life satisfaction (e.g., $r$ = .62-.69; Seligson, Huebner, & Valois, 2005; Seligson, et al., 2003) and positive affect ($r$ = .41, Seligson et al., 2003) and have had acceptable internal consistency reliability when used with adolescents ($\alpha$ = .75, Funk, Huebner, Valois, 2006; $\alpha$ = .81; Zullig, Valois, Huebner, Oeltmann, & Drane, 2001). In the current study, adolescents responded using a five-point response scale (1 = *very dissatisfied* to 5 = *very satisfied*). A mean score, indicating total life satisfaction, was computed with higher scores indicating greater overall life satisfaction. Internal consistency reliability of the BMSLSS score in the current study was strong (α = .80).

***Contribution to community.*** Adolescents' attitudes about making positive contributions to their community were measured with the contribution subscale of the Positive Youth Development Inventory (PYDI; Arnold, Nott, & Meinhold, 2012). The PYDI consists of 58 items designed to measure the five C's of positive youth development (competence, confidence, connection, character, caring) and the sixth emerging element of contribution among adolescents aged 12 to 18 years (Arnold et al., 2012). Respondents use a four-point response scale (1 = *strongly disagree* to 4 = *strongly agree*) to indicate their degree of agreement to seven items about community contribution (e.g., "I take an active role in my community;" "I am someone who gives to benefit others"). Higher mean contribution scores indicate greater degrees of competence in this domain. In previous research, the contribution subscale has demonstrated strong internal consistency reliability (e.g., α = .82 to .89; Pilkauskaite-Valickiene, 2015; Scarbrough & Pritchard, 2013). In the current study, internal consistency reliability of the PYDI was also strong (α = .91).

***Patient Health Questionnaire (PHQ-9).*** Symptoms of depression were measured using the PHQ-9 (Kroenke, Spitzer, & Williams, 2001), a nine-item self-report measure of depressive symptoms corresponding to the nine Diagnostic and Statistical Manual (DSM) criteria for depressive symptoms. Using a four-point response scale (1 = *not at all*, 2 = *several days*, 3 = *more than half the days*, 4 = *nearly every day*), respondents indicated how often they had experienced depressive symptoms within the previous two weeks. Although initially developed for use with adults, the PHQ-9 has preliminary support for use with adolescents (Richardson, McCauley, & Katon, 2009). The PHQ-9 is preferred over the adolescent version of the PHQ (PHQ-A; Zuckerbrot & Jenson, 2006), as the PHQ-9 offers information regarding severity of depressive symptoms. Eight items were the focus of the present study. One item (item 9, “Thoughts that you would be better off dead of or hurting yourself in some way”) was not included in the current study due to school administrators’ concerns about their ability to promptly respond to students who endorsed this item. A mean score was computed, with higher scores indicating greater severity of depressive symptoms. The PHQ-9 has demonstrated adequate psychometric properties, including good sensitivity and specificity for detecting depressive disorders and strong internal consistency reliability ($\alpha = .86$ to .89; Kroenke, Spitzer, Williams, & Löwe, 2010). The internal consistency reliability of the eight PHQ-9 items used in the current study was also strong ($\alpha = .87$).

***Generalized Anxiety Disorder Scale (GAD-7).*** Symptoms of anxiety were assessed using the GAD-7 (Spitzer, Kroenke, Williams, & Löwe, 2006). The GAD-7 is a seven-item self-report measure demonstrating good sensitivity and specificity for detecting generalized anxiety, panic, social anxiety, and post-traumatic stress disorder (Kroenke et al., 2010). Using a four-point response scale (1 = *not at all*, 2 = *several days*, 3 = *more than half the days*, 4 = *nearly every day*), respondents indicated how often they had experienced symptoms related to anxiety within the previous two weeks. A mean score was computed, with higher scores indicating greater severity of anxiety symptoms. The GAD-7 has shown high internal consistency reliability ($\alpha = .92$), construct validity, and discriminant validity with a measure of depression (Spitzer et al., 2006). Internal consistency reliability of the scores in the current study was strong ($\alpha = .90$).

## Data Analytic Strategy

A series of LPAs were conducted to examine the underlying number of latent groups among dual-factor mental health indicators for adolescents in each of Grades 9, 10, and 11 using M*plus* version 7.4 (Muthén & Muthén, 1998-2015). Models were specified using mean composite scores from the four positive mental health domains of the SEHS-S [*belief-in-self* (BIS), *belief-in-others* (BIO), *engaged living* (EL), *emotional competence* (EC)] and two psychological distress dimensions of the abbreviated SDQ [*internalizing risk* (INT) and *externalizing risk* (EXT)] as indicators of well-being and distress, respectively. The model building process requires fitting several possible LPA models for each time point and then comparing the model fit information and substantive interpretation of each model so as to determine which model is most appropriate (Nylund, 2007). In LPA, classes can vary with respect to their indicator means, indicator variances, and covariances between indicators. In the modeling process, indicator means and variances are freely estimated, but indicator-specific variances are commonly held equal across class. However, model specification can differ such that indicator variances can be constrained to be equal across class, or freed to vary (Masyn, 2013). Similarly, within-class indicator covariance (that is, relations between indicators within a given class) are traditionally constrained to be zero, but can be freely estimated. The degree to which the model structure is restricted along these dimensions can impact the number of emerging classes and interpretability of these classes (e.g., whether means, or means and variances, differ across classes). Thus, in the current study, two model structures were examined for each number of latent classes across each year: (a) Model 1 in which item variances are freely estimated but constrained to be equal across classes (i.e., class-invariant) with no within-class indicator covariances (i.e., diagonal), and (b) Model 2 in which indicator variances are freely estimated and are not constrained to be equal across classes (i.e., class-varying) with no within-class indicator covariances (i.e., diagonal).

A small percentage of individuals had missing responses on items contributing to SEHS-S, SDQ, or distal outcome composite score indicators. Missing item responses were accounted for within each subscale before computing composites. Mean composite scores were calculated only for individuals for whom at least 75% of items were answered within a given composite. Indicator level missingness (i.e., due item-level missing data > 25%) is accounted for via Full Information Maximum Likelihood (FIML; Enders & Bandalos, 2001) used in the M*plus* LPA analyses, which allows for item-level (i.e., indicator level) missingness under the assumption that data are missing at random (MAR).

***Class enumeration and retention*.** A series of LPA models were fit in an effort to select a model with a number of classes that sufficiently describe the heterogeneity in the indicators (Masyn, 2013; Nylund, 2007). The number of latent classes was systematically increased by one until empirical support was not evidenced for additional classes, for example due to failures in model convergence or emergence of small or conceptually opaque classes (Nylund et al., 2007b). The model judged to most adequately capture the sample's heterogeneity was selected as the best fitting model for each LPA. In determining the appropriate number of latent classes, Masyn (2013) recommends examining (a) evaluations of absolute fit, (b) evaluations of relative fit, and (c) evaluations of classification. Evaluations of absolute fit, such as standardized residuals of response patterns are not applicable to LPA, thus, relative fit indices were relied upon in the current study.

Evaluations of relative fit assess model fit by comparing a target model to an alternative model with a different number of latent classes and include the information criteria statistics, such as the Bayesian Information Criteria (BIC; Schwartz, 1978), Bayes Factor (BF), correct model probability (cmP), Bootstrap Likelihood ratio Test (BLRT; McLachlan & Peel, 2000), and Vuong Lo Mendel Rubin LRT (VLMR-LRT; Vuong, 1989). When interpreting the BF values between 1 and 3 offer weak evidence, between 3 and 10 offer moderate evidence, and greater than 10 offer strong evidence for the current model (Wasserman, 1997). Larger cmP values indicate a greater likelihood of the model being the correct model out of all models tested (Masyn, 2013). The BLRT and the VLMR-LRT tests examine the fit of a *k*-class model with a *k*-1 class solution, with non-significant *p*-values indicating support for the *k*-1 class solution. With regard to information criteria statistics, superior model fit is indicated by lower values. In a simulation study examining the performance of likelihood-based tests and information criterion indices, Nylund, Asparouhov, and Muthén (2007), found that the BLRT and BIC indices provide the most reliable estimates of model fit. Thus, these fit indices were given the most weight. Accuracy of classification of individuals to latent classes within a given model was examined based upon estimates of posterior class probability (i.e., the likelihood of each individual's membership in a given class, based upon his or her pattern of responses) and relative entropy (Ramaswamy, DeSarbo, Reibstein, & Robinson, 1993). High entropy has been associated with values close to .80 (Clark & Muthén, 2009), with values closer to 1 indicating superior classification precision (Masyn, 2013). Each of the above criteria was evaluated in selecting and interpreting models for each year in the present study.

***Specification of conditional models with demographic covariates and distal outcomes.*** Following specification of unconditional, cross-sectional LPA models for Grades 9, 10, and 11, and a final model has been selected for each grade year, covariates of gender and ethnicity (Latinx, non-Latinx) and distal academic and social-emotional outcomes were included in the model. When covariates and distal outcomes are examined concurrently, the manual BCH method is recommended (Asparouhov & Muthén, 2015). The manual BCH method for specification of covariates and distal outcomes controls for the relation between the demographic covariates and social-emotional distal outcomes when examining the independent relations between the latent class and each of the covariates and distal outcomes. The BCH method is preferred and has proven robust when distal outcomes are continuous (Bakk & Vermunt, 2014; Muthén & Muthén, 1998-2015). By using weights that reflect the measurement error due to imperfect class assignment, the BCH method uses a multiple group analysis to avoid shifts in latent classes that can occur when covariates and distal outcomes are included in latent class models. Using this method, (a) the latent class indicator is regressed onto the demographic covariates, (b) the distal outcomes are regressed onto the latent class indicator, and (c) the distal outcomes are regressed onto the covariates. When examining the relation between the latent classes and the covariates, the covariates maintain their dichotomous coding (i.e., 0, 1). However, when examining the direct relation between the distal outcomes and the covariates, the covariates are mean centered to allow for ease of interpretation of the conditional means produced for each outcome. That is, means, conditioned on (i.e., controlling for) the covariates, are estimated for each outcome for each emerging complete mental health class for each of Grades 9, 10, and 11. The estimated means are then compared across class to identify any significant differences between classes on the distal outcomes measured.

# Results

## Latent Profile Analyses: Empirical Identification of Dual-Factor Mental Health Classes

Average responses on the mental health indicators and predictive validity outcomes are presented in Table 1. Cross-sectional LPA models were run for each of the three years of data (Grade 9, 10, and 11). A one-class model was tested first and then additional models with more latent classes were explored. Given the LPA framework, both the class-invariant, diagonal (Model 1) and class-varying, diagonal (Model 2) model structures were tested. Table 2 presents the information used to evaluate each model, including fit statistics (i.e., log likelihood, BIC, BF, cmP, and *p* values for the LMRT and BLRT), entropy values, and class prevalence proportions. Examining the results for Grade 9, the BIC (2587.56), cmP (.75), and BF (3.18) indicate that the four-class class-invariant, diagonal model fit best. Although the five-class solution also had support (BIC = 2589.87, BF = 23.80), examination of class prevalence information indicated that the additional fifth class explained variance in an unreliably small percentage of people (1.0% or 3.32 people). Thus, the four-class solution was chosen as the best fitting model. Model 2 structures for Grade 9, 10, and 11 models with greater than four, three, or two classes, respectively across years, demonstrated failed log likelihood convergence for 20% to 82% of runs, indicating model instability despite the produced fit criteria. Thus, best fitting models were selected with Model 1 structure for each grade year. Further examination of fit criteria across each grade year also supported a four class solution for Grade 10 (BIC = 2227.50, BF = 11.42, cmP = .85) and Grade 11 (BIC = 2305.36, LMRT $p = .01$). The observed entropy values of the best-fitting four-class solutions approximated high levels of entropy, with values ranging from .78 (Grades 9 and 10) to .82 (Grade 11), and indicate that for at least 78% to 82% of the time, individuals were correctly classified in latent classes (Clark & Muthén, 2009). Therefore, a four-class model was deemed the optimal model for Grades 9, 10, and 11.

The profile plots of the estimated mean values for each mental health domain are presented in Figure 1. Based on the pattern of mean scores across the well-being (i.e., SEHS-S) and distress (i.e., SDQ) domains, the following labels are offered for the four emerging classes across each year: *complete mental health* (30.5%, Grade 9; 40.8%, Grade 10; 20.5%, Grade 11) with the highest means on the well-being domains and the lowest means on the distress domains, *moderately mentally healthy* (43.4%, 32.0%, 44.3%, respectively) with high-average means on the well-being indicators and low means on the distress domains, *symptomatic but content* (20.3%, 21.2%, 31.3%, respectively) also with high-average well-being but with higher mean scores on the distress indicators, and *troubled* (5.7%, 6.0%, 3.8%, respectively) with below-average well-being and average to above-average scores on the distress indicators. When examining the size of each class across years, the *troubled* class consistently had the smallest percentage of students. Most students exhibited high or high-average scores on the well-being indicators with low levels of reported distress on the distress indicators (i.e., *complete mental health* or *moderately mentally healthy*). Overall, a larger percentage of students fell into mental health classes characteristic of higher levels of distress by Grade 11 (i.e., *troubled* or *symptomatic but content*). Youth in mental health classes characteristic of higher levels of distress, particularly in Grades 10 and 11, tended to report higher levels of internalizing distress as compared to externalizing distress.

Table 3 presents the average posterior class probability (AvePP; Masyn, 2013) of students being classified into each mental health class, given their classification into one mental health class. For example, in Grade 9, the probability of individuals in the *moderately* *mentally healthy* class being classified into the *complete mental health* class was .08. The values in the shaded cells presented on the diagonal for each grade level illustrate the probability that members of a given class would be classified into that class (i.e., classification accuracy). The accuracy of classification for each mental health class across years was high (> .80).

**Gender and Ethnic Differences in Group Classification with LPA**

Using the optimal fitting four-class model identified for each year, the manual BCH process was implemented to examine the associations gender and ethnicity have with students' dual-factor mental health across the three high school years. Using the manual BCH approach, the logit values of each indicator were fixed to the values produced during the model enumeration process detailed above, thereby preventing any changes in latent profiles due to inclusion of the covariates. Then, the dichotomized gender and ethnicity covariates were regressed on the latent class variable. Three covariate comparisons were made for each year: (a) the likelihood of being in the *moderately mentally healthy* class compared to the *complete mental health* class, (b) the likelihood of being in the *symptomatic but content* class compared to the *complete mental health* class, and (c) the likelihood of being in the *troubled* class compared to the *complete mental health* class. Table 4 summarizes the logits, standard errors (SE), *p*-values, and odds ratios for each of the covariates included in the model. The *complete mental health* class was used as the normative comparison group. Negative logit values indicate that for a given covariate, students were more likely to be categorized in the *complete mental health* reference group rather than the comparison class when $p < .05$. Significant ethnicity effects were evident in Grade 9, such that students identifying as Hispanic or Latinx were more likely to be in the *moderately mentally healthy* ($p = .023$), *symptomatic but content* ($p$ = .001), and *troubled* ($p$ = .018) classes than in the *complete mental health* class. In Grade 10, Hispanic or Latinx students continued to be more likely to be in the *symptomatic but content* ($p$ = .003) and *troubled* ($p$ = .006) classes than in the *complete mental health* class, but were no longer significantly more likely to be in the *moderately mentally healthy* class. In Grade 11, Hispanic or Latinx students were more likely to be in the *symptomatic but content* class ($p$ = .002) than in the *complete mental health* class, but were no more likely than non-Latinx students to be in the other two mental health classes as compared to the *complete mental health* class.

There was also a significant association of gender with mental health class. In Grade 9, female students were more likely to be in the *symptomatic but content* ($p$ = .001) class than in the *complete mental health* class. However, females were no more likely to be in the *moderately mentally healthy* or *troubled* classes than in the *complete mental health* class ($p$ > .05). In Grade 10, females remained more likely to be in the *symptomatic but content* ($p$ = .001) class than in the *complete mental health* class. No gender effects remained in Grade 11; males and females were equally likely to be in the four mental health classes in Grade 11.

**Differences in Academic and Social-Emotional Outcomes based on LPA Classification**

To examine the predictive validity of the classes yielded with LPA, we examined whether academic and social-emotional indicators differed across the four mental health classes. Prosocial contribution to community, life satisfaction, depression symptoms, anxiety symptoms, and self-reported grades, as measured in Grade 12, were treated as distal outcomes in these analyses. That is, we examined differences between mental health classes in each of Grade 9, 10, and 11 using the five academic and social-emotional outcome indicators. Moreover, because both covariates and distal outcomes were examined in the current analyses, the manual BCH method was used so that the relation between the covariates and distal outcomes was controlled when examining differences on the distal outcomes based on latent class membership. Thus, the results presented reflect the effect of latent class membership on each distal outcome at the average level of the gender and ethnicity covariates while controlling for the direct relation between the distal outcomes and gender and ethnicity.

Table 5 presents the class specific means and standard errors on each of the academic and social-emotional outcomes for the Grade 9, 10, and 11 analyses, after controlling for the direct relations between the outcomes and the gender and ethnicity covariates. To test which mental health classes differed in their mean outcome scores, a Wald Test was conducted on all between-group comparisons. A conservative *p*-value (.01) was used to adjust for increased error due to multiple tests. Few differences between classes in each of Grades 9, 10, and 11 were observed with respect to self-reported grades. No significant differences were observed for Grade 9, with the Grade 10 and 11 differences reflecting higher grades for students in the *complete mental health* or *moderately mentally healthy* classes with respect to the *symptomatic but content* class.

Class specific differences were observed for the positive mental health outcomes of prosocial contribution to community and life satisfaction. Students in the *complete mental health* and *moderately mentally healthy* classes had significantly greater prosocial contribution than the *symptomatic but content* and *troubled* classes. The Grade 9 and Grade 11 *complete mental health* and *moderately mentally healthy* classes similarly reported higher average levels of life satisfaction in Grade 12 than the *symptomatic but content* and *troubled* classes. The Grade 10 *complete mental health* class had significantly greater life satisfaction than all other classes. In Grade 11, adolescents in the *symptomatic but content* and *troubled* classes significantly differed, with students in the *symptomatic but content* class who reported higher levels of well-being also reporting greater levels of life satisfaction.

With regards to symptoms of psychopathology, as measured via average frequency of PHQ-9 depression symptoms and GAD-7 anxiety symptoms in Grade 12, students in the *symptomatic but content* and *troubled* classes tended to report more frequent symptoms of depression and anxiety, on average, than did students in the *complete mental health* and *moderately mentally healthy* classes. Patterns were largely consistent across both depression and anxiety outcomes for classes in each of Grades 9, 10, and 11. However, minor variations were observed between classes for each grade year. For example, when Grade 12 outcomes were examined for Grade 9 classes, contrary to classes in the other grade years, students in the Grade 9 *symptomatic but content* class had significantly higher levels of depression in Grade 12, but not anxiety, than students in the *troubled* class. However, of the Grade 11 classes, students in the *troubled* class had significantly higher levels of anxiety in Grade 12, but not depression, than did students in the *symptomatic but content* class.

Overall, groups reporting higher levels of well-being with low levels of distress tended to exhibit more positive outcomes on both the positive mental health and negative mental health indicators. Similarly, groups reporting higher levels of distress tended to experience poorer outcomes on the negative indicators of mental health. The *complete mental health* class was generally associated with the most positive outcomes up to three years later (i.e., better grades, higher average scores on positive mental health outcomes, lower average scores on negative mental health outcomes). However, the *complete mental health* class did not unanimously experience more positive outcomes than the *moderately mentally healthy* class, who had slightly lower average well-being. Similarly, though not always exhibiting significant differences between one another or with the other two classes, the *symptomatic but content* and *troubled classes* tended to experience poorer outcomes, especially with regard to negative mental health outcomes.

## Discussion

The current study set out to examine an empirical approach to mental health classification using the dual factor framework. A series of LPAs using well-being and distress indicators were examined simultaneously to determine the number of emerging metal health groups in each of Grades 9, 10, and 11. Once optimal LPA models were selected for each grade year, the relation between gender and ethnicity covariates on mental health class membership was examined. The validity and predictive utility of the emerging, empirically defined dual-factor mental health classes was also examined as related to academic outcomes (i.e., self-reported grades) and positive (i.e., prosocial contribution to community, life satisfaction) and negative (i.e., symptoms of depression and anxiety) indicators of social-emotional well-being and thriving measured in Grade 12.

Previous dual-factor research has most often classified students into four groups based on logically determined cut points for well-being and distress indicators (e.g., Greenspoon & Saklofske, 2001; Suldo & Shaffer, 2008). In the current study, we relied on patterns in students' reports about their own mental health functioning to inform the most relevant mental health grouping. In each of Grades 9, 10, and 11 the LPA results supported a four-class solution, representative of four mental health groups with varying levels of well-being and distress: *complete mental health* (i.e., above average strengths, below average distress), *moderately mentally healthy* (i.e., average strengths, below average distress), *troubled* (i.e., below average strengths, average to above average distress), and *symptomatic but content* (i.e., average strengths, average to above average distress). The emerging latent classes were examined at three time points across the high school years to determine whether the construct of dual-factor mental health remained stable over time; that is, its structural stability. Over three years of high school, we found structural stability in the latent dual-factor mental health construct. The four-class solution consisting of a *complete mental health*, *moderately mentally healthy*, *symptomatic but content*, and *troubled* class was replicated for each of Grade 9, 10, and 11. Despite minor fluctuations observed in the average scores for the well-being and distress indicators for each class, the substantive interpretation for each solution is consistent over time.

Consistent with previous dual-factor research, each of a *complete mental health*, *troubled*, and *symptomatic but content* class emerged in the current study. However, inconsistent with previous cut score and empirical classification work (e.g., Rebelez-Ernst, 2015), a languishing or vulnerable group, indicative of low well-being and low distress, did not emerge in the current study. Rather, the fourth emerging mental health group (i.e., students who are *moderately mentally healthy*) reported average to above average well-being and below average distress. As can be seen in the profile plots of the emerging latent classes in Figure 1, this fourth emerging group reported similar levels of well-being as the *symptomatic but content* class in Grades 9 and 10 (although it was more differentiated from the *symptomatic but content* group in level of well-being in Grade 11), but markedly lower levels of distress, particularly as related to internalizing problems. The inability to detect a languishing group in the current study may reflect sample specific characteristics such that the small sample size impacts the ability of the current analyses to adequately detect a robust group of students following a languishing pattern when well-being and distress indicators are examined simultaneously. That is, a very small number of students may fit this profile, but their limited size makes them statistically unreliable and difficult to detect within an LPA framework. Analyses including a much larger number of youth would have more statistical power to detect additional small, but homogenous, groups of students. However, the current results may also indicate that a languishing mental health profile is an artifact of the cut point approach to classification, wherein predetermined criteria utilized to classify students as having high or low well-being may label students whose scores fall near the cut point as having low well-being despite the similarity in their scores to students in other mental health groups. Replication of the current study's results with larger, independent samples is warranted.

The patterns observed in levels of strengths (i.e., the well-being indicators) in the current study indicate that understanding adolescents' well-being may be more nuanced than what has been described in previous dual-factor work. For example, rather than simply indicating lower versus higher well-being via a predetermined cut point, the LPA results reveal a gradient of well-being, with three of the four emerging mental health groups consistently differing in their average levels of social-emotional strengths. Moreover, empirically defining complete mental health groups allows for a group of students with the highest levels of well-being and the lowest levels of distress to be distinguished (i.e., *complete mental health*) from those students with high-average levels of well-being and low levels of distress (*moderately mentally healthy*). Within the dichotomous cut- point approach to classification, students in the *moderately mentally healthy* class may have been considered to have complete mental health.

Although the same four classes emerged across the exploratory LPA analyses for each of Grades 9, 10, and 11, indicating consistency in the construct of dual-factor mental health over time, the proportions of adolescent students comprising each mental health class exhibited variability. In each grade year, the majority of students were classified into the *complete mental health* and *moderately mentally healthy* classes. However, in Grades 9 and 11 *moderately mentally healthy* students represented over 40% of the sample, whereas the *complete mental health* group was largest (41%) in Grade 10. The *troubled* class exhibited consistency in size whereas the *symptomatic but content* group increased over time, reaching 31% by Grade 11 compared to 20% in Grade 9. Similarly, the *complete mental health* class was its smallest (21%) in Grade 11, compared to 31% in Grade 9 and 41% in Grade 10. These fluctuations in class prevalence observed over time suggest that movement is occurring across classes from year to year. The proportions of students in the *complete mental health* and *moderately mentally healthy* classes in the current study are similar to rates reported by Keyes (2006) who found that, among adolescents aged 15 to 18, most reported being moderately mentally healthy (55%) followed by flourishing (40%; i.e., complete mental health). However, the percentage of students in emerging *complete mental health* classes in the current study (Grade 9 = 31%, Grade 10 = 41%, Grade 11 = 21%) is consistently smaller than percentages reported in previous dual-factor research using a cut score approach [e.g., 42% (Venning et al., 2013) to 64% (Lyons et al., 2012)]. This result suggests that the number of youth exhibiting complete mental health may be overestimated when cut-point criteria are applied to youth's mental health data rather than when groups are formed based on patterns in observed data.

When examining gender and ethnicity in relation to mental health class, we found decreasing effects of each covariate over time, with ethnicity having stronger effects than gender on class membership. For example, in early high school (Grades 9 and 10, but not Grade 11), female students were more likely than male students to be classified into the *symptomatic but content class* compared to the *complete mental health* class. Given that students in the *symptomatic but content* class reported higher mean levels of internalizing distress than externalizing distress, as seen in Figure 1, and that females are more likely to experience internalizing problems than males (e.g., Meirkangas et al., 2009), these results are not surprising. Similarly, in early high school, students identifying as Latinx or Hispanic were found to be less likely to be in the *complete mental health* class than in the other mental health classes. Although the effect of ethnicity diminished in Grade 11, Latinx or Hispanic students remained more likely to be in the *symptomatic but content* class as compared to the *complete mental health* class. The decreasing effects of gender and ethnicity are indicative of two patterns. First, the predictive power of gender and ethnicity covariates is strongest in Grade 9, at the transition to high school. Research suggesting that girls (e.g., Finn & Rock, 1997) and Latinx students (e.g., Benner & Graham, 2009) experience more distress in the transition to high school may account for the observed differences in girls and Latinx students belonging to classes reporting distress in Grade 9. Moreover, a majority of the Latinx participants in the current study (80.9%) also experience socioeconomic disadvantage; thus, these students may be more likely to experience distress given socioeconomic hardship that is conflated with their ethnic identification. Second, the reduced association between gender and ethnicity over time provides further evidence that students may be changing classes over time. Significant covariate results indicate that the proportions of males/females or Latinx/Non-Latinx students in the two classes being compared differs. In order for these comparisons to become nonsignificant, students would need to enter or exit classes such that the ratio of males/females or Latinx/Non-Latinx became similar across the two comparison classes. Thus, additional longitudinal analyses examining the stability of individuals' dual-factor mental health class membership is needed.

Our findings also supported class differences in Grade 12 reports of academic achievement (grades) and positive (prosocial contribution to community and life satisfaction) and negative (depression symptoms and anxiety symptoms) mental health indicators. Students in classes indicative of higher average scores on well-being indicators and lower average scores on distress indicators tended to have higher scores on positive indicators of mental health and lower scores on negative indicators of mental health over time, indicating that the four emerging classes are valid representations of dual-factor mental health constructs. Consistent with previous research, we found that students in the *complete mental health* class experienced the most favorable academic and social-emotional outcomes across grade years, followed by students in the *moderately mentally healthy* class, with these two groups differing significantly from one another in approximately half of the comparisons made. Also consistent with previous research, students in the *troubled* class tended to experience the least favorable outcomes, although their self-reported outcomes were not always statistically significantly different from youth in the *symptomatic but content* class or from the *moderately mentally healthy* and *complete mental health* classes. However, given the much smaller size of the *troubled* class in the current study (i.e., approximately 6% or 20 people in Grade 9 and 10, and 4% or 12 people in Grade 11), comparisons made between the *troubled* group and the other mental health groups were likely underpowered. Replication of the present findings with larger samples is needed. Overall, more differences between latent classes on Grade 12 outcomes were observed in Grade 11, indicating that the predictive power of latent mental health classes is strongest within one year prior, as opposed to two or three years prior to measurement of the outcomes of interest.

Previous dual-factor mental health research has also indicated that, among youth experiencing distress, those with higher levels of well-being (i.e., in the *symptomatic but content* group) tend to exhibit more positive outcomes (e.g., Antaramian et al., 2010). In the current study, this effect was observed in relation to anxiety symptoms and life satisfaction (particularly in Grade 11), such that youth in the *symptomatic but content* class, exhibited more positive outcomes than youth in the *troubled* class. However, students in the *symptomatic but content* class also, on average, reported lower levels of internalizing distress than did youth in the *troubled* class. Thus, it is unclear if the presence of higher levels of well-being or lower levels of internalizing distress led to more positive outcomes for this group of students. An advantage of the empirical approach to classification, however, is that it allows meaningful differences in average responses on a given indicator to emerge across mental health groups; differences that are not acknowledged when groups created by cut scores are treated as homogenous.

**Implications for Research and Practice**

The present study contributes to a growing body of research supporting a comprehensive approach to mental health assessment that includes indicators of both well-being and distress. Using an empirical approach to complete mental health classification enabled identification of variability in well-being and distress observed for four emerging mental health groups. Although, on the surface, confirming the presence of four empirically defined mental health groups parallels what has been illustrated in previous dual-factor research, empirically identifying groups as opposed to using logically determined cut points allowed for meaningful variation in levels of well-being and distress indicators to be observed across groups. These results indicate that the cut-point approach to forming mental health groups may incompletely capture the complexity in students' dual-factor mental health profiles. Thus, the current results extend previous research on dual-factor mental health and offer continued support for examining both well-being and distress in universal screening efforts that can be used to inform prevention and early intervention within school settings. Moreover, the empirical dual-factor classification research (e.g., Kim et al., 2016; Rebelez-Ernst, 2015), including the current study, highlight limitations in a binary cut-score approach to classification.

A shortcoming of previous dual-factor research, and, in general, logical cut-point approaches to classification, is that potentially heterogeneous groups are treated as homogenous (i.e., anyone scoring above the $31^{st}$ percentile on a measure being indicated as having high well-being; e.g., Kim et al., 2016, Nylund et al., 2007b). Moreover, when predetermined cut points are used, individuals with miniscule differences in scores indicative of well-being or distress who vary on either side of a given cut point are classified into different mental health groups, despite little practical differences in the two scores (i.e., $T$ = 59 is classified as low distress whereas $T$ = 61 indicates high distress; Antaramian et al., 2010; Lyons et al., 2012; Suldo & Shaffer, 2008; Thalji, 2013). Inaccuracy in classification arises when the pattern of experiences for individuals scoring on either side of the cut point reflects more similarities than differences, despite their classification into different groups. Although there is error associated with both LPA and cut point approaches to classification, cut point approaches do not allow for examination of the probability of members of one class being classified into (i.e., being similar to) another class. Using an empirically defined approach to classification allows us to examine the accuracy with which students are placed into groups via estimates of the likelihood of being classified into a given class based on one's most likely latent class membership. Using empirically identified latent classes in the current study, we were able to model the error associated with classification and could examine the likelihood of individuals indicated as members in one mental health class being classified into another mental health class on an aggregate level (Table 3). As observed in the current study, the empirically defined mental health groups exhibited strong accuracy in classification. However, future research is needed to compare differences in classification that may arise when a cut score versus empirical approach to classification is used. For example, investigations can compare the distribution of students assigned to LPA produced mental health classes as compared to group assignment based on cut scores as well as any differences in the predictive validity of each mental health class with later outcomes. In addition, examining the likelihood of membership in each empirically defined mental health class on an individual level (rather than at an aggregate level, as done in the current study) can be used to further examine accuracy of classification of an LPA versus cut-score approach.

Overall, the results of the current study call for further examination of cut-score approaches to classification used to interpret universal complete mental health screening data and to inform intervention. Although practitioners may lack the resources needed to evaluate schoolwide or grade-specific screening assessment data using LPA (e.g., classification results are not currently easily generated without advanced statistical software and applications;

practitioners may need additional training to understand LPA classification and its relation to later outcomes and intervention), the results of the current study highlight that a dichotomous, cut-score approach to complete mental health classification may obscure meaningful variation in students' complete mental health profiles. Rather, if limited to using cut-score approaches due to the ease and efficiency of this approach, practitioners may wish to utilize additional cut points, especially with regard to students' well-being, resulting in more than four groups. Concurrently, scholars, practitioners, and other school mental health stakeholders are called upon to investigate and develop techniques for translating LPA classification parameters into a usable format for organizing dual-factor mental health data collected at schools intended to guide intervention. For example, data scoring and software programs are needed that provide LPA-informed classification results, including probability of an individual's membership within a given mental health class.

**Limitations & Future Directions**

Several limitations of this study are important to acknowledge. First, although adequate in size for the current analyses, the present sample was restricted in geographic diversity, which limits the generalizability of our findings. The sample consisted of students attending only one school in central California and was limited in size by attrition between Grade 9 and Grade 12, when the outcome measures were administered. Additionally, although the percentage of students representing the smallest *troubled* group was consistent with estimates of the proportion of youth who are identified as having severe mental health concerns via universal screening (Moore et al., 2015), the sample size of the current study resulted in a small number of students comprising the *troubled* group, thus limiting the power to detect differences between this group and the other mental health groups. Additional research is needed with larger samples that are more geographically diverse and that include students from additional ethnic and racial backgrounds.

Second, the measures used as indicators of well-being and distress, and for the academic and social-emotional outcomes, relied solely on self-report. Thus, results may be influenced by a mono-method bias, wherein a spurious association between variables may be observed due to self-report use for both mental health indicators and outcomes (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003), and social desirability bias (Huang, Liao, & Chang, 1998). In addition, although adolescents are increasingly recognized as ideal informants of their own internal states (e.g., Smith, 2007), other research suggests that adolescents may be unideal informants of their own externalizing behavior (e.g., Smith, Pelham, Gnagy, Molina, & Evans, 2000). The representation of externalizing problems in the emerging mental health profiles may be limited by adolescents' self-reported accounts of their externalizing behavior. The lower rates of externalizing problems compared to internalizing problems observed in the current study may reflect participants' underestimation of their own externalizing behavior or reflect the attrition of students with higher externalizing problems from the study, rather than indicate a relative lack of externalizing problems in the present sample. Additional research utilizing other forms of measurement, including school-reported grades and achievement data (e.g., standardized test scores) and teacher or parent reported levels of externalizing problems is needed.

Finally, each year after universal screening was completed at the partnering high school, data was shared with the school regarding students' level of risk and well-being so as to inform schoolwide, small-group, or individual interventions implemented by the school-staff. However, data were not available regarding whether, of what kind, and with what regularity individuals in the current study may have participated in intervention. Moreover, data were collected once per year and represent students' functioning at the time at which data were collected. Variations in class proportions observed over Grades 9, 10, and 11 may have been impacted by intervention or other temporary or acute life experiences that impacted adolescents' self-report of their own mental health. Recognizing the plethora of factors that may impact adolescents' mental health, additional research examining individual or contextual features impacting current experiences of complete mental health is recommended.

As the goal of the current study was to empirically identify and evaluate dual-factor complete mental health classes among adolescents in high school, the longitudinal analyses of the current paper are limited in their ability to inform stability of individuals' dual-factor mental health and in asserting use of LPA approaches to classification over cut-point approaches. Although the analyses of the present study make an important contribution to dual-factor mental health research by validating the structural stability of empirically defined mental health classes based upon indicators of both well-being and distress, an important next step will be to investigate the stability of individuals' patterns of dual-factor mental health over the high school years. For example, research answering questions related to the stability of individuals' mental health group membership and in what direction changes may occur over time is needed to further understand dual-factor mental health. Research has emerged examining the longitudinal stability of adolescents dual-factor complete mental health using a cut-point approach over one year or less (e.g., Kelly, Hills, Heubner, & McQuillin, 2012; McMahan, 2012); however, research examining stability of individuals' complete mental health using empirically defined groups and over more than one year is lacking. In addition, research comparing classification and predictive validity of empirically derived versus cut score defined dual-factor mental health groups is important for informing applied classification efforts within school settings that impact intervention.

Understanding mental health as comprised of indicators of well-being and distress is important in comprehensive efforts to address risk and promote youth thriving. When used as part of universal mental health screening, information gained from assessment of youths' complete mental health can be used to inform intervention at each level of a comprehensive service delivery system, including school-wide, small-group, and individualized interventions intended to ameliorate psychopathology and support development of social-emotional strengths and student well-being. The current study, using an empirical approach to classification of youths' complete mental health provides initial information that can be used in determining how to classify students into distinct mental health groups for intervention and follow-up efforts after screening assessments. Continuing to explore alternative approaches to classification of complete mental health, as well as the longitudinal stability of complete mental health are important for informing school-based efforts to support students' positive mental health and well-being.

## References


Adler, R. P., & Goggin, J. (2005). What do we mean by "civic engagement"? *Journal of Transformative Education, 3*(3), 236–253. doi:10.1177/1541344605276792

Angold, A., Erkanli, A., Farmer, E. M., Fairbank, J. A., Burns, B. J., Keeler, G., & Costello, E. J. (2002). Psychiatric disorder, impairment, and service use in rural African American and white youth. *Archives of General Psychiatry, 59*(10), 893–901. doi:10.1001/archpsyc.59.10.893

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

Arnold, M. E., Nott, B. D., & Meinhold, J. L. (2012). *The Positive Youth Development Inventory Full Version.* Corvallis, OR: Oregon State University.

Asparouhov T., & Muthén B. (2015). Auxiliary variables in mixture modeling: Using the BCH method in M*plus* to estimate a distal outcome model and an arbitrary secondary model. *Mplus Web Notes, 21*(2), 1–22.

Bakk, Z., & Vermunt, J. K. (2014). Robustness of stepwise latent class modeling with continuous distal outcomes. *Structural Equation Modeling: A Multidisciplinary Journal, 23,* 20–31. doi:10.1080/10705511.2014.955104

Benner, A. D., & Graham, S. (2009). The transition to high school as a developmental process among multiethnic urban youth. *Child Development, 80*(2), 356–376. doi:10.1111/j.1467-8624.2009.01265.x

Billig, S. H. (2002). Revitalizing K-12 schools: The case for service-learning. In R. M. Lerner, D. Wertlieb, & F. Jacobs (Eds.), *Handbook of applied developmental science (Vol. 4): Adding value to youth and family development—The engaged university and professional and academic outreach* (pp. 153–172). Thousand Oaks, CA: Sage.

Brock, S. E. (2015). Mental health matters. *Communiqué, 43*(7), 13–15.

Browne, M.W., & Cudeck, R. (1989). Single sample cross-validation indices for covariance structures. *Multivariate Behavioral Research, 24*, 445–455. doi:10.1207/s15327906mbr2404_4

California Department of Education. (n.d.). *California school district secondary school survey results fall 2009/spring 2010: Core module A.* Retrieved from http://chks.wested.org/resources/a-text_0910.pdf

Clark, S. L., & Muthén, B. (2009). *Relating latent class analysis results to variables not included in the analysis.* Unpublished manuscript, University of California Los Angeles, Los Angeles, CA.

Deković, M., Buist, K. L., & Reitz, E. (2004). Stability in changes in problem behavior during adolescence: Latent growth analysis. *Journal of Youth and Adolescence, 33*, 1–12. doi:10.1023/A:1027305312204

Dickey, W. C., & Blumberg, S. J. (2001). Revisiting the factor structure of the Strengths and Difficulties Questionnaire. *Journal of the American Academy of Child and Adolescent Psychiatry, 43*, 1159–1167. doi:10.1097/01.chi.0000132808.36708.a9

Dowdy, E., Furlong, M. J., Eklund, K., Saeki, E., & Ritchey, K. (2010). Screening for mental health and wellness: Current school-based practices and emerging possibilities. In B.

Doll, W. Pfohl, & J. Yoon (Eds.), *Handbook of youth prevention science* (pp. 70–95). New York, NY: Routledge.

Dowdy, E., Furlong, M. J., Raines, T., Bovery, B., Kauffman, B., Kamphaus, R., … & Murdock, J. (2015). Enhancing school-based mental health services with a preventive and promotive approach to universal screening for complete mental health. *Journal of Educational and Psychological Consultation, 25,* 1–20. doi:10.1080/10474412.2014.929951

Dowdy, E., Nylund-Gibson, K., Felix, E. D., Morovati, D., Carnazzo, K. W., & Dever, B. V. (2014). Long-term stability of screening for behavioral and emotional risk. *Educational and Psychological Measurement, 74*(3), 453–472. doi:10.1177/0013164413513460

Duchesne, S., Vitaro, F., Larose, S., & Tremblay, R. E. (2008). Trajectories of anxiety during elementary-school years and the prediction of high school noncompletion. *Journal of Youth and Adolescence, 37,* 1134–1146. doi:10.1007/s10964-007-9224-0

Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal, 8,* 430–457. doi:10.1207/S15328007SEM0803_5

Ferdinand, R. F., Verhulst, F. C., & Wiznitzer, M. (1995). Continuity and change of self-reported problem behaviors from adolescence into young adulthood. *Journal of the American Academy of Child and Adolescent Psychiatry, 34*(5), 680–690. doi:10.1097/00004583-199505000-00020

Finn, J. D., & Rock, D. A. (1997). Academic success among students at risk for school failure. *Journal of Applied Psychology, 82*, 277–290. doi:10.1037/0021-9010.82.2.221

Frazier, T. W., Youngstrom, E. A., Clutting, J. J., & Watkins, M. W. (2007). ADHD and achievement: Meta-analysis of the child, adolescent, and adult literatures and a concomitant study with college students. *Journal of Learning Disabilities, 40,* 49–65. doi:10.1177/00222194070400010401

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

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

Furlong, M. J., You, S., Renshaw, T. L., Smith, D. C., & O'Malley, M. D. (2014). Preliminary development and validation of the Social and Emotional Health Survey for secondary students. *Social Indicators Research*, *117,* 1011–1032. doi:10.1007/s11205-013-0373-0

Furr, R. M., & Funder, D. (1998). A multimodal analysis of personal negativity. *Journal of Personalityand Social Psychology, 74*, 1580–1591. doi:10.1037/0022-3514.74.6.1580

Galambos, N., Leadbeater, B., & Barker, E. (2010). Gender differences in and risk factors for depression in adolescence: A 4-year longitudinal study. *International Journal of Behavioral Development, 28,* 16–25. doi:10.1080/01650250344000235

Gilman, R., & Huebner, E. S. (2003). A review of life satisfaction research with children and adolescents. *School Psychology Quarterly, 18*(2), 192–205. doi:10.1521/scpq.18.2.192.21858

Glover, T. A., & Albers, C. A. (2007). Considerations for evaluating universal screening assessments. *Journal of School Psychology, 45,* 117–135. doi:10.1016/j.jsp.2006.05.005

Goodman, R. (1997). The Strengths and Difficulties Questionnaire: A research note. *Child Psychology & Psychiatry & Allied Disciplines, 38*(5), 581–586. doi:10.1111/j.1469-7610.1997.tb01545.x

Goodman, R. (1999). The extended version of the Strengths and Difficulties Questionnaire as a guide to child psychiatric caseness and consequent burden. *Journal of Child Psychology, Psychiatry, and Allied Disciplines, 40,* 791–799. doi:10.1111/1469-7610.00494

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

Hale, W. M. III, Raaijmakers, W., Muris, P., van Hoof, A., & Meeus, W. (2008). Developmental trajectories of adolescent anxiety disorder symptoms: A 5-year prospective community study. *Journal of the American Academy of Child & Adolescent Psychiatry*, *47*, 556–564. doi:10.1097/CHI.0b013e3181676583

Hu, L., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods, 3*, 424–453. doi:10.1037/1082-989X.3.4.424

Huang, C., Liao, H., & Chang, S. (1998). Social desirability and the clinical self-report inventory: Methodological reconsideration. *Journal of Clinical Psychology, 54,* 517–528. doi:10.1002/(SICI)1097-4679(199806)54:4<517::AID-JCLP13>3.0.CO;2-I

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

Huebner, E. S. (2004). Research on assessment of life satisfaction of children and adolescents. *Social Indicators Research, 66*, 3–33. doi:10.1023/B:SOCI.0000007497.57754.e3

Huebner, E. S., Funk, B. A., & Gilman, R. (2000). Cross-sectional and longitudinal psychosocial correlates of adolescent life satisfaction reports. *Canadian Journal of School Psychology, 16,* 53–64. doi:10.1177/082957350001600104

Kamphaus, R. W., & Reynolds, C. R. (2007). *BASC-2 Behavioral and Emotional Screening System.* Minneapolis, MN: Pearson Assessment.

Kamphaus, R. W., Reynolds, C. R., & Dever, B. V. (2014). Behavioral and mental health screening. In R. J. Kettler, T. A. Glover, C. A. Albers, & K. A. Feeney-Kettler (Eds.), *Universal screening in educational settings: Evidence-based decision making for schools* (pp. 249–273). Washington, DC: American Psychological Association.

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

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

Kim, E. K., Dowdy, E., Furlong, M. J., & You, S. (2016). Mental health profiles and quality of life among Korean adolescents. *School Psychology International* (Advance Online Publication). doi:10.1177/0143034316682296

Kim, E. K., Furlong, M. J., Dowdy, E., & Felix, E. D. (2014). Exploring the relative contributions of strength and distress components of dual-factor complete mental health screening. *Canadian Journal of School Psychology, 29*(2), 127–140. doi:10.1177/0829573514529567

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine, 16*, 606–613. doi:10.1046/j.1525-1497.2001.016009606.x

Kroenke, K., Spitzer, R. L., Williams, J. B. W., & Löwe B. (2010). The Patient Health Questionnaire somatic, anxiety, and depressive symptom scales: A systematic review. *General Hospital Psychiatry, 32,* 345–359. doi:10.1016/j.genhosppsych.2010.03.006

LaGuardia, J. G., & Ryan, R. M. (2002). What adolescents need: A self-determination theory perspective on development within families, school, and society. In F. Pajares & T. Urdan (Eds.), *Academic motivation of adolescents* (pp. 193–219). Greenwich, CT: Information Age.

Laursen, B., & Hoff, E. (2006). Person-centered and variable centered approaches to longitudinal data. *Merrill-Palmer Quarterly, 52,* 377–389. doi:10.1353/mpq.2006.0029

Lent, R. W. (2004). Toward a unifying theoretical and practical perspective on well-being and psychosocial adjustment. *Journal of Counseling Psychology*, *51*(4), 482–509. doi:10.1037/0022-0167.51.4.482

Lewinsohn, P., Redner, J., & Seeley, J. (1991). The relationship between life satisfaction and psychosocial variables: New perspectives. In F. Strack, M. Argyle, & N. Schwartz (Eds.), *Subjective well-being* (pp. 193–212). New York, NY: Plenum.

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

Maton, K. I. (1990). Meaningful involvement in instrumental activity and well-being: Studies of older adolescents and at risk urban teen-agers. *American Journal of Community Psychology, 18,* 297–320. doi:10.1007/BF00931306

Masten, A. S., Roisman, G. I., Long, J. D., Burt, K. B., Obradović, J., Riley, J. R. … & Tellegen, A. (2005). Developmental cascades: Linking academic achievement and internalizing and externalizing symptoms over 20 years. *Developmental Psychology, 41*(5), 733–746. doi:10.1037/0012-1649.41.5.733

Masyn, K. E. (2013). Latent class analysis and finite mixture modeling. In T. D. Little (Ed.), *The Oxford handbook of quantitative methods* (pp. 551–611). New York, NY: Oxford University Press.

McLachlan, G., & Peel, D. (2000). *Finite mixture models*. New York, NY: Wiley.

McMahan, M. M. (2012). *A longitudinal examination of high school students' group membership in a dual-factor model of mental health: Stability of mental health status* *and predictors of change* (Doctoral Dissertation). Retrieved from University of South Florida Scholar Commons (4369).

Merikangas, K. R., Jian-ping, H., Burstein, M., Swanson, S. A., Avenevoli, S., Lihong, C., … & Swendsen, J. (2010). Lifetime prevalence of mental disorders in US adolescents: Results from the National Comorbidity Study-Adolescent Supplement (NCS-A). *Journal of the American Academy of Child and Adolescent Psychiatry, 49*(10), 980–989. doi:10.1016/j.jaac.2010.05.017

Merikangas, K. R., Nakamura, E., & Kessler, R. C. (2009). Epidemiology of mental disorders in children and adolescents. *Dialogues in Clinical Neuroscience, 11*, 7–20.

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

Muthén, L. K., & Muthén, B. O. (1998-2015). *Mplus user's guide* (7th Ed.). Los Angeles, CA: Muthén & Muthén.

Nylund, K. L. (2007). *Latent transition analysis: Modeling extensions and an application to peer victimization* (Doctoral Dissertation). Retrieved from http://www.statmodel.com/download/Nylund%20dissertation%20Updated1.pdf

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

Nylund, K., Bellmore, A., Nishina, A., Graham, S. (2007b). Subtypes, severity, and structural stability of peer victimization: What does latent class analysis say? *Child Development, 78*(6), 1706–1722. doi:10.1111/j.1467-8624.2007.01097.x

Obradović, J., Burt, K. B., & Masten, A. S. (2010). Testing a dual cascade model linking competence in symptoms over 20 years from childhood to adulthood. *Journal of Child & Adolescent Psychology, 39*(1), 90–102. doi:10.1080/15374410903401120

Obradović, J., van Dulmen, M. H. M., Yates, T. M., Carlson, E. A., & Egeland, B. (2006). Developmental assessment of competence from early childhood to middle adolescence. *Journal of Adolescence, 29*, 857–889. doi:10.1016/j.adolescence.2006.04.009

Park, N., Peterson, C., & Seligman, M. E. (2004). Strengths of character and well-being. *Journal of Social and Clinical Psychology, 23*(4), 603-619. doi:10.1521/jscp.23.5.603.50748

Pilkauskaite-Valickiene, R. The role of character, confidence, and connection on contribution and subjective well-being. *Procedia – Social and Behavioral Sciences, 197*, 265–270. doi:10.1016/j.sbspro.2015.07.134

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88,* 879–903. doi:10.1037/0021-9010.88.5.879

Radke-Yarrow, M., Zahn-Waxler, C., & Chapman, M. (1983). Children's prosocial dispositions and behavior. In E. M. Hetherington (Ed.), *Handbook of child* *psychology (Vol. 4.): Socialization, personality, and social development* (pp. 469–546). New York, NY: Wiley.

Ramaswamy, V., Desarbo, W. S., Reibstein, D. J., & Robinson, W. T. (1993). An empirical pooling approach for estimating marketing mix elasticities with PIMS data. *Marketing Science, 12*(1), 103–124. doi:10.1287/mksc.12.1.103

Rapee, R. M., Schniering, C. A., & Hudson, J. L. (2009). Anxiety disorders during childhood and adolescence: Origins and treatment. *Annual Review of Clinical Psychology, 5*, 311–341. doi:10.1146/annurev.clinpsy.032408.153628

Rebelez-Ernst, J. L. (2015). *Capturing complete mental health among adolescents: Investigation of covitality latent class typologies.* Doctoral Dissertation, University of California Santa Barbara. http://search.proquest.com/openview/5aef7dbb1061568d84ad824b093b91fb/1?pq-origsite=gscholar&cbl=18750&diss=y

Renshaw, T. L. (2015). Psychometric properties of the Social and Emotional Health Survey with a small sample of academically at-risk adolescents. Advanced online publication*. Journal of Psychoeducational Assessment*. doi:10.1177/0734282915614495

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

Reschly, A. L., Huebner, E. S., Appleton, J. J., & Antaramian, S. (2008). Engagement as flourishing: The contribution of positive emotions and coping to adolescents' engagement at school and with learning. *Psychology in the Schools, 45,* 419–431. doi:10.1002/pits.20306

Richardson, L., McCauley, & E., Katon, W. (2009). Collaborative care for adolescent depression: a pilot study. *General Hospital Psychiatry, 31,* 36–45. doi:10.1016/j.genhosppsych.2008.09.019

Roberts, R. E., & Chen, Y. W. (1995). Depressive symptoms and suicidal ideation among Mexican-origin and Anglo adolescents. *Journal of the American Academy of Child and Adolescent Psychiatry, 34,* 81–90. doi:10.1097/00004583-199501000-00018

Roberts, R. E., Roberts. C. R., & Chen, Y. R. (1997). Ethnocultural differences in prevalence of adolescent depression. *American Journal of Community Psychology, 25,* 95–110. doi:10.1097/00004583-199501000-00018

Ruchkin, V., Jones, S., Vermeiren, R., & Schwab-Stone, M. (2008). The Strengths and Difficulties Questionnaire: The self-report version in American urban and suburban youth. *Psychological Assessment, 20*, 175–182. doi:10.1037/1040-3590.20.2.175

Scales, P. C., & Benson, P. L. (2005). Prosocial orientation and community service. In K. A. Moore & L. H. Lippman (Eds.), *What do children need to flourish?* (pp. 339–356). New York, NY: Springer.

Scales, P. C., Benson, P. L., Roehlkepartain, E. C., Sesma, A., & van Dulmen, M. (2006). The role of developmental assets in predicting academic achievement: A longitudinal study. *Journal of Adolescence*, *29*, 691–708. doi:10.1016/j.adolescence.2005.09.001

Scarbrough. S., & Pritchard, M. (2013). Positive youth development and substance use in emerging adults. *McNair Scholars Research Journal, 9*(1), 61–66.

Schwartz, G., (1978). Estimating the dimension of a model. *The Annals of Statistics, 6,* 461–464. doi:10.1214/aos/1176344136

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

Seligson, J., Hueber, E. S., & Valois, R. F. (2005). An investigation of the brief life satisfaction scale with elementary school children. *Social Indicators Research, 73*(3), 355–374. doi:10.1007/s11205-004-2011-3

Smith, S. R. (2007). Making sense of multiple informants in child and adolescent psychopathology: A guide for clinicians. *Journal of Psychoeducational Assessment, 25*, 139–149. doi:10.1177/0734282906296233

Smith, B. H., Pelham Jr., W. E., Gnagy, E., Molina, B., & Evans, S. (2000). The reliability, validity, and unique contributions of self-report by adolescents receiving treatment for attention-deficit/hyperactivity disorder. *Journal of Consulting and Clinical Psychology, 68*(3), 489–499. doi:10.1037//0022-006X.68.3.489

Spitzer, R. L., Kroenke, K., Williams, J. B. W., Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. *Archives of Internal Medicine, 166*, 1092–1097. doi:10.1001/archinte.166.10.1092

Stoep, A. V., McCauley, E., Thompson, K. A., Herting, J. R., Kuo, E. S., Stewart, D. G., … Kushen, S. (2005). Universal emotional health screening at the middle school transition. *Journal of Emotional and Behavioral Disorders, 13,* 213–223. doi:10.1177/10634266050130040301

Suldo, S. M., & Huebner, E. S. (2006). Is extremely high life satisfaction during adolescence advantageous? *Social Indicators Research, 78,* 179–203. doi:10.1007/s11205-005-8208-2

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

Suldo, S., Thalji, A., & Ferron, J. (2011). Longitudinal academic outcomes predicted by early adolescents' subjective well-being, psychopathology, and mental health status yielded from a dual factor model. *The Journal of Positive Psychology: Dedicated to Furthering Research and Promoting Good Practice*, *6*, 17–30. doi:10.1080/17439760.2010.536774

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

Thalji, A. L. (2013). *A dual-factor model of mental health in high school students: Group characteristics and social functioning* (Doctoral Dissertation). Retrieved from University of South Florida Scholar Commons (4239).

Venning, A., Wilson, A., Kettler, L., & Eliott, J. (2013). Mental health among youth in South Australia: A survey of flourishing, languishing, struggling, and floundering. *Australian Psychologist, 48*, 299–310. doi:10.1111/j.1742-9544.2012.00068.x

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

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

Wasserman, L. (1997). *Bayesian model selection and model averaging*. Paper presented at Mathematical Psychology Symposium on "Methods for Model Selection," Bloomington, Indiana.

Westerhof, G. B., & Keyes, C. L. M. (2010). Mental illness and mental health: The two-continua model across the lifespan. *Journal of Adult Development, 17*, 110–119. doi:10.1007/s10804-009-9082-y

World Health Organization. (2016, April). *Mental health: Strengthening our response (fact sheet).* Retrieved from http://www.who.int/mediacentre/factsheets/fs220/en/

You, S., Furlong, M. J., Dowdy, E., Renshaw, T., Smith, D. C., & O'Malley, M. D. (2014). Further validation of the Social and Emotional Health Survey for high school students. *Applied Quality of Life Research, 9,* 997–1015. doi:10.1007/s11482-013-9282-2

Zuckerbrot, R. A., & Jensen, P. S. (2006). Improving recognition of adolescent depression in primary care. *Archives of Pediatrics and Adolescent Medicine, 160,* 694–704. doi:10.1001/archpedi.160.7.694

Zullig, K. J., Valois, R. F., Huebner, E. S., Oeltmann, J. E., & Drane, J. W. (2001). Relationship between perceived life satisfaction and adolescents' substance abuse. *Journal of Adolescent Health, 29*(4), 279–288. doi:10.1016/S1054-139X(01)00269-5

Table 1

*Means and Standard Deviations of Mental Health Indicators and Outcomes*

| | Grade 9 | | Grade 10 | | Grade 11 | | Grade 12 | |
|---|---|---|---|---|---|---|---|---|
| | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| SEHS-S | | | | | | | | |
| Belief in Self | 2.87 | 0.50 | 3.05 | 0.44 | 3.04 | 0.53 | | |
| Belief in Others | 3.14 | 0.56 | 3.34 | 0.50 | 3.29 | 0.59 | | |
| Emotional Competence | 2.98 | 0.48 | 3.22 | 0.44 | 3.24 | 0.49 | | |
| Engaged Living | 3.31 | 0.68 | 3.39 | 0.60 | 3.36 | 0.68 | | |
| SDQ | | | | | | | | |
| Internalizing | 1.64 | 0.44 | 1.51 | 0.42 | 1.57 | 0.48 | | |
| Externalizing | 1.72 | 0.42 | 1.50 | 0.45 | 1.45 | 0.45 | | |
| Prosocial Contribution to Community | | | | | | | 4.66 | 0.99 |
| Life Satisfaction | | | | | | | 4.97 | 0.85 |
| Depression Symptoms | | | | | | | 1.58 | 0.59 |
| Anxiety Symptoms | | | | | | | 1.57 | 0.68 |
| Self-Reported Grades | | | | | | | 6.44 | 1.53 |

*Note:* SEHS-S = Social Emotional Health Survey – Secondary; SDQ = Strengths and Difficulties Questionnaire.

Table 2

*Information Used to Evaluate Tested LPA Dual-Factor Mental Health Models*

| Model | Number of classes | Log likelihood | BIC | *p*-value of BLRT | *p*-value of LMRT | BF | cmP | Entropy | Class Prevalence |
|---|---|---|---|---|---|---|---|---|---|
| Grade 9 - Model 1 (*n* = 332) | 1 | -1464.48 | 2998.61 | - | - | <.001 | <.001 | - | 1.00 |
| | 2 | -1299.40 | 2709.10 | <.001 | <.001 | <.001 | <.001 | 0.74 | .44, .55 |
| | 3 | -1231.61 | 2614.15 | <.001 | **0.01** | <.001 | <.001 | 0.85 | .05, .35, .60 |
| | 4 | -1197.99 | **2587.56** | <.001 | 0.55 | 3.18 | **0.75** | 0.78 | .06, .31, .20, .43 |
| | 5 | -1178.83 | 2589.87 | <.001 | 0.10 | **23.80** | 0.24 | 0.81 | .01, .09, .19, .27, .44 |
| | 6 | -1161.69 | 2596.21 | <.001 | 0.31 | <.001 | 0.01 | 0.81 | .01, .08, .12, .12, .28, .39 |
| Grade 9 - Model 2 (*n* = 332) | 1 | -1464.48 | 2998.61 | - | - | <.001 | <.001 | - | 1.00 |
| | 2 | -1264.67 | 2674.46 | <.001 | <.001 | <.001 | <.001 | 0.82 | .33, .67 |
| | 3 | -1195.92 | 2612.43 | <.001 | **0.03** | 0.23 | 0.10 | 0.75 | .23, .33, .44 |
| | 4* | -1156.72 | 2609.50 | <.001 | 0.20 | 0.98 | 0.45 | 0.79 | .05, .25, .32, .39 |
| | 5* | -1118.97 | **2609.47** | <.001 | 0.26 | **>100** | **0.45** | 0.82 | .05, .09, .23, .23, .41 |
| | 6* | -1095.71 | 2638.41 | 0.01 | 0.62 | <.001 | <.001 | 0.81 | .05, .07, .11, .18, .27, .32 |
| Grade 10 - Model 1 (*n* = 324) | 1 | -1283.37 | 2636.10 | - | - | <.001 | <.001 | - | 1.00 |
| | 2 | -1101.50 | 2312.83 | <.001 | <.001 | <.001 | <.001 | 0.75 | .49, .51 |
| | 3 | -1040.96 | 2232.21 | <.001 | **0.02** | 0.09 | 0.08 | 0.82 | .07, .41, .53 |
| | 4 | -1018.37 | **2227.50** | <.001 | 0.39 | **11.42** | **0.85** | 0.78 | .06, .21, .32, .41 |
| | 5 | -1000.57 | 2232.37 | <.001 | 0.38 | 799.91 | 0.07 | 0.76 | .07, .09, .17, .32, .35 |
| | 6 | -987.02 | 2245.74 | 0.01 | 0.54 | <.001 | <.001 | 0.78 | .02, .07, .09, .16, .32, .34 |
| Grade 10 - Model 2 (*n* = 324) | 1 | -1283.37 | 2636.10 | - | - | <.001 | <.001 | - | 1.00 |
| | 2 | -1058.99 | 2262.49 | <.001 | <.001 | <.001 | <.001 | 0.80 | .42, .58 |
| | 3* | -990.87 | 2201.41 | <.001 | 0.05 | 0.01 | 0.01 | 0.79 | .15, .35, .51 |
| | 4* | -948.16 | **2191.13** | <.001 | **<0.001** | **>100** | 0.99 | 0.80 | .09, .13, .38, .40 |
| | 5* | -919.23 | 2208.43 | <.001 | 0.11 | 40.49 | <.001 | 0.84 | .10, .12, .13, .29, .36 |
| | 6* | -885.36 | 2215.83 | <.001 | 0.03 | <.001 | <.001 | 0.84 | .05, .09, .12, .13, .24, .37 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Grade 11 - Model 1 (*n* = 291) | 1 | -1379.66 | 2827.40 | - | - | <.001 | <.001 | - | 1.00 |
| | 2 | -1161.17 | 2430.13 | <.001 | **<.001** | <.001 | <.001 | 0.83 | .38, .62 |
| | 3 | -1104.56 | **2356.62** | <.001 | 0.21 | <.001 | <.001 | 0.86 | .05, .43, .52 |
| | 4 | -1059.07 | **2305.36** | <.001 | **0.01** | 0.03 | <.001 | 0.82 | .04, .21, .31, .44 |
| | 5 | -1035.57 | 2298.07 | <.001 | 0.39 | 0.17 | 0.14 | 0.81 | .03, .10, .20, .22, .44 |
| | 6 | -1013.92 | 2294.49 | <.001 | 0.67 | <.001 | **0.85** | 0.82 | .03, .09, .12, .18, .22, .36 |
| Grade 11 - Model 2 (*n* = 291) | 1 | -1379.66 | 2827.40 | - | - | <.001 | <.001 | - | 1.00 |
| | 2* | -1127.24 | 2396.32 | <.001 | **<0.001** | <.001 | <.001 | 0.80 | .44, .56 |
| | 3* | -1033.93 | **2283.45** | <.001 | 0.20 | <.001 | <.001 | 0.86 | .19, .33, .48 |
| | 4* | -979.96 | 2249.26 | <.001 | 0.37 | - | **1.00** | 0.87 | .06, .16, .30, .48 |

*Note*. Bolded values indicate preferred model for a given fit index. Shaded rows indicate model selected for each year.
*log likelihood starting values did not converge, indicating model instability.

Table 3

*Average Posterior Class Probability of Most Likely Latent Class Membership by Latent Mental Health Class*

| | | Classification Probability | | | |
|---|---|---|---|---|---|
| Grade | Most Likely Class Membership | 1 | 2 | 3 | 4 |
| Grade 9 | 1. Complete Mental Health | 0.94 | 0.06 | 0.01 | 0.00 |
| | 2. Moderately Mentally Healthy | 0.08 | 0.86 | 0.05 | 0.01 |
| | 3. Symptomatic but Content | 0.01 | 0.16 | 0.83 | 0.01 |
| | 4. Troubled | 0.00 | 0.08 | 0.07 | 0.85 |
| Grade 10 | 1. Complete Mental Health | 0.94 | 0.04 | 0.02 | 0.00 |
| | 2. Moderately Mentally Healthy | 0.08 | 0.85 | 0.08 | 0.00 |
| | 3. Symptomatic but Content | 0.04 | 0.15 | 0.81 | 0.01 |
| | 4. Troubled | 0.00 | 0.04 | 0.09 | 0.85 |
| Grade 11 | 1. Complete Mental Health | 0.86 | 0.14 | 0.00 | 0.00 |
| | 2. Moderately Mentally Healthy | 0.05 | 0.90 | 0.05 | 0.00 |
| | 3. Symptomatic but Content | 0.00 | 0.08 | 0.91 | 0.01 |
| | 4. Troubled | 0.00 | 0.00 | 0.02 | 0.98 |

*Note*. Shaded cells indicate accuracy of classification.

Table 4

*Log Odds Coefficients and Odds Ratios for the Four-Class Models with Gender and Ethnicity as Predictors Using the Complete Mental Health Class as the Comparison Group*

| Grade | Mental Health Class | Effect | Logit | *SE* | *t* | Odds Ratio | *p*-value |
|---|---|---|---|---|---|---|---|
| Grade 9 | *Moderately Mentally Healthy* | | | | | | |
| | | Female | -0.43 | 0.33 | -1.28 | 0.65 | 0.201 |
| | | Latinx | 0.76 | 0.34 | 2.28 | 2.14 | **0.023** |
| | *Symptomatic but Content* | | | | | | |
| | | Female | 1.41 | 0.43 | 3.26 | 4.10 | **0.001** |
| | | Latinx | 1.25 | 0.39 | 3.20 | 3.49 | **0.001** |
| | *Troubled* | | | | | | |
| | | Female | -0.02 | 0.61 | -0.03 | 0.98 | 0.973 |
| | | Latinx | 1.60 | 0.68 | 2.36 | 4.95 | **0.018** |
| Grade 10 | *Moderately Mentally Healthy* | | | | | | |
| | | Female | -0.43 | 0.35 | -1.21 | 0.65 | 0.225 |
| | | Latinx | 0.59 | 0.34 | 1.75 | 1.80 | 0.080 |
| | *Symptomatic but Content* | | | | | | |
| | | Female | 1.65 | 0.48 | 3.46 | 5.21 | **0.001** |
| | | Latinx | 1.24 | 0.42 | 2.97 | 3.46 | **0.003** |
| | *Troubled* | | | | | | |
| | | Female | 0.79 | 0.55 | 1.44 | 2.20 | 0.151 |
| | | Latinx | 1.72 | 0.62 | 2.77 | 5.58 | **0.006** |
| Grade 11 | *Moderately Mentally Healthy* | | | | | | |
| | | Female | 1.81 | 0.40 | 0.45 | 6.11 | 0.652 |
| | | Latinx | 0.67 | 0.42 | 1.60 | 1.95 | 0.110 |
| | *Symptomatic but Content* | | | | | | |
| | | Female | 0.38 | 0.39 | 0.97 | 1.46 | 0.332 |
| | | Latinx | 1.27 | 0.41 | 3.11 | 3.56 | **0.002** |
| | *Troubled* | | | | | | |
| | | Female | 0.75 | 0.77 | 0.97 | 2.12 | 0.334 |
| | | Latinx | 1.50 | 0.80 | 1.87 | 4.48 | 0.062 |

*Note.* Bolded values indicate $p < .05$.

Table 5

*Means and Standard Errors of Academic and Social-Emotional Distal Outcomes in Grade 12 Across Mental Health Classes*

| | | Grade 12 Outcomes (Response Scale) | | | | |
|---|---|---|---|---|---|---|
| Grade | Mental Health Class | Self-Reported Grades (1-8) | Contribution to Community (1-6) | Life Satisfaction (1-6) | Depression Symptoms (1-4) | Anxiety Symptoms (1-4) |
| Grade 9 ($n$ = 332) | Complete Mental Health (30.5%) | 6.47 (.16)$_{a}$ | 5.04 (.11)$_{a}$ | 5.18 (.10)$_{a}$ | 1.58 (.07)$_{a}$ | 1.54 (.08)$_{a}$ |
| | Moderately Mentally Healthy (43.4%) | 6.63 (.12)$_{a}$ | 4.61 (.09)$_{a}$ | 5.07 (.07)$_{a}$ | 1.48 (.05)$_{a}$ | 1.42 (.06)$_{a}$ |
| | Symptomatic but Content (20.3%) | 6.03 (.20)$_{a}$ | 4.37 (.13)$_{b}$ | 4.58 (.14)$_{b}$ | 1.91 (.10)$_{b}$ | 2.02 (.13)$_{b}$ |
| | Troubled (5.7%) | 6.45 (.44)$_{a}$ | 4.15 (.20)$_{b}$ | 4.57 (.30)$_{ab}$ | 1.37 (.14)$_{a}$ | 1.52 (.17)$_{ab}$ |
| Grade 10 ($n$ = 324) | Complete Mental Health (40.8%) | 6.72 (.12)$_{a}$ | 4.96 (.09)$_{a}$ | 5.35 (.07)$_{a}$ | 1.39 (.05)$_{a}$ | 1.32 (.05)$_{a}$ |
| | Moderately Mentally Healthy (32.0%) | 6.44 (.16)$_{ab}$ | 4.56 (.11)$_{b}$ | 4.83 (.10)$_{b}$ | 1.45 (.07)$_{ac}$ | 1.55 (.08)$_{ab}$ |
| | Symptomatic but Content (21.2%) | 6.03 (.22)$_{b}$ | 4.39 (.15)$_{c}$ | 4.63 (.14)$_{b}$ | 2.12 (.11)$_{b}$ | 2.01 (.13)$_{b}$ |
| | Troubled (6.0%) | 6.00 (.44)$_{ab}$ | 4.16 (.19)$_{bc}$ | 4.50 (.21)$_{b}$ | 1.84 (.15)$_{bc}$ | 2.03 (.20)$_{b}$ |
| Grade 11 ($n$ = 291) | Complete Mental Health (20.5%) | 6.79 (.21)$_{a}$ | 5.32 (.13)$_{a}$ | 5.47 (.12)$_{a}$ | 1.29 (.07)$_{a}$ | 1.34 (.10)$_{a}$ |
| | Moderately Mentally Healthy (44.3%) | 6.60 (.12)$_{a}$ | 4.88 (.08)$_{b}$ | 5.20 (.06)$_{a}$ | 1.44 (.05)$_{a}$ | 1.43 (.06)$_{a}$ |
| | Symptomatic but Content (31.3%) | 6.29 (.14)$_{ab}$ | 4.12 (.10)$_{c}$ | 4.52 (.09)$_{b}$ | 1.82 (.07)$_{b}$ | 1.82 (.07)$_{b}$ |
| | Troubled (3.8%) | 5.10 (.51)$_{b}$ | 3.64 (.29)$_{c}$ | 3.57 (.33)$_{c}$ | 2.36 (.20)$_{b}$ | 2.51 (.24)$_{c}$ |

*Note:* Means that do not share subscripts differ at $p < .01$.

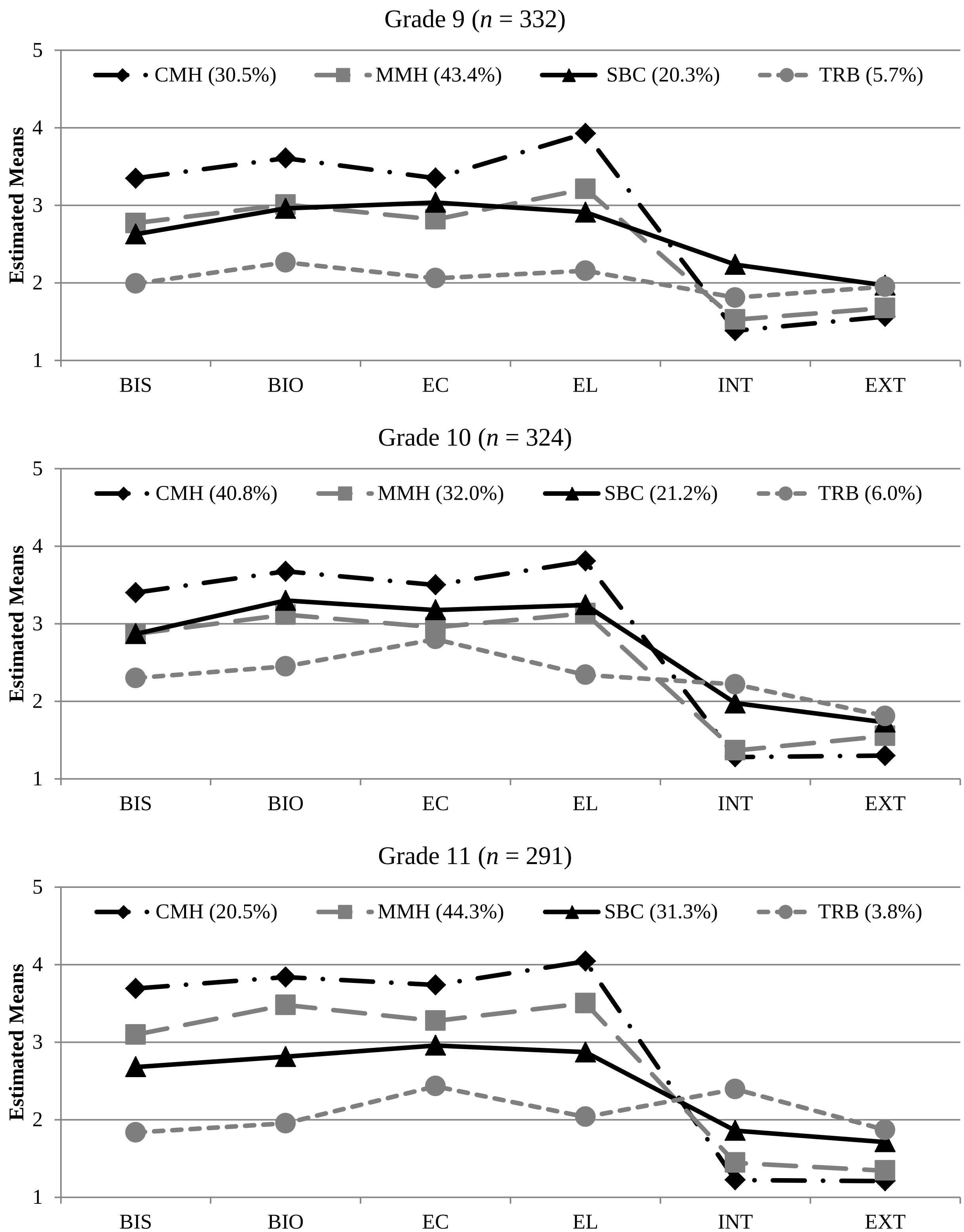


*Figure 1*. Dual-factor mental health profile plots for the four-class models for Grade 9 through Grade 11. Class size information is presented in the legend. (*Note*. BIS = belief in self, BIO = belief in others, EC = emotional competence, EL = engaged living, INT = internalizing, EXT = externalizing. CMH = complete mental health class, MMH = moderately mentally healthy class, SBC = symptomatic but content class, TRB = troubled class.) The mean-value range for BIS, BIO, and EC was 1 to 4; for EL was 1 to 4.67; and for INT and EXT was 1 to 3.

**Study 2:**

**A Latent Transition Analysis of the Longitudinal Stability of Dual-Factor Mental Health in Adolescence**

**Abstract**

Dual-factor models of mental health focusing on well-being and psychopathology are increasingly supported. Although the cross-sectional literature regarding dual-factor mental health and the relation of mental health group membership to later youth outcomes is growing, research examining longitudinal trends in dual-factor mental health is needed. The current study used latent profile analysis (LPA) to empirically identify dual-factor mental health profiles at each of Grades 9 through 12 and latent transition analysis (LTA) to examine stability of profiles over the four academic years. A sample of 875 adolescents from two cohorts (Cohort A = Grades 9 to 11, Cohort B = Grades 10 to 12) reported on their social-emotional strengths and psychological distress. Cross-sectional LPAs for each grade year resulted in four mental health profiles: *complete mental health*, *moderately mentally healthy*, *symptomatic but content*, and *troubled*. An LTA model assuming full measurement invariance, nonstationary transitions, and controlling for cohort indicated that the *complete mental health* profile exhibited the most stability, followed by *moderately mentally healthy* and *symptomatic but content* profiles. The *troubled* profile exhibited the least stability. Less than 24% of participants remained in the same mental health class across in all years; however, the most stable patterns were youth who remained in the *complete mental health* (10%) and *moderately mentally healthy* (9%) profiles. Findings support regular monitoring of students' dual-factor mental health to accurately inform mental health promotion, prevention, and intervention efforts.

*Keywords*: dual-factor mental health, stability, adolescent, latent profile analysis (LPA), latent transition analysis (LTA)

## A Latent Transition Analysis of the Longitudinal Stability of Dual-Factor Mental Health in Adolescence

Dual-factor models describe mental health as being influenced by the interaction between well-being and psychopathology (Greenspoon & Saklofske, 2001; Keyes, 2002; Suldo & Shaffer, 2008). Research supporting dual-factor mental health is growing and substantiates the need to consider indicators of well-being and psychopathology in school-based mental health assessment, prevention, and intervention efforts. Whereas research examining the stability of psychopathology (e.g., Overbeek, Vollebergh, Meeus, Engels, & Luijpers, 2001) and well-being (e.g., Huebner, Funk, & Gilman, 2000) independently is well established, research examining the longitudinal stability of dual-factor mental health is limited. Currently, only three identified studies have examined the longitudinal stability of dual-factor mental health (Compton, 2016; Kelly, Hills, Heubner, & McQuillin, 2012; McMahan, 2012). However, stability among these samples was examined over only five-month, seven-month, and one-year periods. Thus, it remains unknown to what degree adolescents' dual-factor mental health status remains stable or changes beyond one year. The present study aims to address these gaps in the current understanding of dual-factor mental health by providing the first examination of the stability of adolescents' dual-factor mental health across the high school years. Results of this study will contribute to the growing understanding of dual-factor mental health, and can inform efforts in identifying and supporting youths' mental health needs in schools.

### Defining Mental Health

Traditional approaches to mental health assessment have aligned with a medical model, defining mental health as the absence of psychopathology (Greenspoon & Saklofske, 2001; Keyes, 2002). This approach places mental health and mental illness at opposite ends of a single continuum, and lends itself to the assumption that mental health arises from the absence of mental illness. With the rise of positive psychology, definitions of mental health began to include an explicit focus on the presence of positive health indicators, such as well-being (Seligman, 2002) or social-emotional assets/strengths (Scales, 1999), with mental health implying not only the absence of illness, but also wellness promotion. Contemporary mental health researchers increasingly recommend conceptualizing mental health more broadly, such that mental health is understood (a) as being distinct from mental illness, and (b) to include an explicit focus on indicators of well-being (e.g., Seligman & Csikszentmihalyi, 2000). Expanded views of mental health consider that the absence of disease may represent a necessary, but not sufficient, condition for mental health (Jahoda, 1958).

Contemporary, dual-factor (e.g., Greenspoon & Saklofske, 2001) or two-continua (e.g., Westerhof & Keyes, 2010) models of mental health propose that positive (i.e., strengths, subjective well-being) and negative (i.e., distress, psychopathology) indicators of mental health lie on separate, yet related continua, and that each be taken into consideration when attending to youths' mental health (Suldo & Shaffer, 2008). Using this framework, at least four discrete mental health groups have been reported across elementary (Compton, 2016; Greenspoon & Saklofske, 2001), middle (Antaramian, Huebner, Hills, & Valois, 2010; Suldo & Shaffer, 2008), and high school students (McMahan, 2012; Suldo, Thalji-Raitano, Kiefer, & Ferron, 2016), as well as across transition age adults (Eklund, Dowdy, Jones, & Furlong, 2011; Renshaw & Cohen, 2014). These groups have been defined as: (a) troubled (i.e., high levels of psychopathology and low levels of well-being), (b) complete mental health (i.e., low levels of psychopathology and high levels of well-being), (c) symptomatic but content (i.e., high levels of psychopathology and high levels of well-being), and (d) vulnerable or languishing (i.e., low levels of psychopathology and low levels of well-being). Whereas complete mental health and troubled groups are identified using the traditional problem-based definition of mental health, symptomatic but content and vulnerable groups highlight the need to attend to both well-being and psychopathology in mental health assessment and intervention.

**Advantages of a Dual-Factor Approach**

Research has supported the benefit of dual-factor over problem-focused approaches to mental health classification, assessment, and intervention. When well-being and distress are examined concurrently, discrepancies among the defined mental health groups are observed across important youth outcomes. For example, middle school students with complete mental health were found to have superior reading achievement, academic self-perceptions, motivation, attendance, engagement, and social relationships and functioning (e.g., peer and teacher support) compared to youth in the other three mental health groups (e.g., Antaramian et al., 2010; Suldo & Shaffer, 2008). Similarly, high-school students with complete mental health experienced better academic attitudes, perceptions of physical health, social support, satisfaction with romantic relationships, and identity development (Suldo et al., 2016). Meaningful variation along both the well-being and psychopathology dimensions has been related to differences in academic and social-emotional outcomes such that an additive effect of well-being on youths' outcomes has also been supported. For example, in comparison to vulnerable students, youth with complete mental health exhibited superior outcomes, indicating that merely the absence of psychopathology is insufficient for optimal functioning

(Antaramian et al., 2010; Suldo & Shaffer, 2008; Suldo et al., 2016). In addition, with respect to youth experiencing psychopathology, those with higher levels of well-being (i.e., symptomatic but content) tended to have more positive outcomes (e.g., social relationships, academic self-perceptions, perceived physical health, social support, identity development) when compared to youth with similar levels of psychopathology, but low levels of well-being (i.e., troubled; Suldo & Shaffer, 2008; Suldo et al., 2016).

Overall, a variety of positive outcomes are associated with complete mental health, with low levels of psychopathology proving insufficient for optimal development. Conversely, youth exhibiting low levels of well-being and high levels of psychopathology tended to experience the poorest outcomes across studies (Antaramian et al., 2010; Greenspoon & Saklofske, 2001; Renshaw & Cohen, 2014; Suldo & Shaffer, 2008; Suldo, Thalji, & Ferron, 2011). Thus, when youth's mental health is examined within a dual-factor framework, it is possible to comprehensively understand youth's mental health functioning. Then, interventions appropriate for meeting needs related to both well-being and psychopathology can be identified or designed, such that youths' complete mental health is promoted (Suldo & Shaffer, 2008).

**Longitudinal Stability of Dual-Factor Mental Health**

Despite the growing evidence in support of dual-factor approaches, current research is limited by its cross-sectional nature. The longitudinal stability of psychopathology and well-being independently is well established. Although some variation is evident in stability estimates across various indicators of psychopathology (e.g., $r$ = .48 for attention problems, .57 for aggressive behavior; Verhulst & van Wattum, 1993) and well-being ($\beta$ = .20 for emotional well-being, .94 for cognitive competence; Obradović, van Dulmen, Yates, Carlson,

& Egeland, 2006), research generally supports moderate levels of stability over periods of one year or more (e.g., $r$ = .53 to .60 for internalizing problems, externalizing problems, and well-being indicators; Deković, Buist, & Reitz, 2004; Ferdinand, Verhulst, & Wiznitzer, 1995; Huebner, 2004; Huebner et al., 2000; Obradović et al., 2006). However, research examining the stability of dual-factor mental health is limited, despite its importance for informing recommendations for frequency of assessment and school-based prevention and intervention efforts. Therefore, the goal of the present study was to examine the longitudinal stability of dual-factor mental health classifications across the high school years.

Only three known studies have investigated the longitudinal stability of dual-factor mental health, with this research being conducted with elementary (Compton, 2016), middle (Kelly, Hills, Huebner, & McQuillin, 2012), and high school students (McMahan, 2012). Table 1 summarizes the group-based stability and transition patterns observed in these studies. Kelly and colleagues (2012) first examined the stability of dual-factor mental health group membership among adolescents in Grades 7 and 8 and over a five-month period. Using norm-referenced cut-point criteria, participants were classified into four groups based on the intersection of high or low subjective well-being and psychopathology. The four groups formed at Time 1 and Time 2 were: (a) complete mental health (64% at Time 1, 68% at Time 2), (b) vulnerable (8%, 9%), (c) symptomatic but content (20%, 16%), and (d) troubled (8%, 7%). Overall, 69% of the middle school students remained in the same mental health group at both Time 1 and Time 2. Across the four groups, the complete mental health group exhibited the greatest stability, with 85% of those in the complete mental health group at Time 1 remaining in that group five months later. Moderate levels of stability were observed between the symptomatic but content (42%) and troubled groups (47%), and the vulnerable group exhibited the lowest level of stability (29%). An examination of instability patterns revealed that, among the least stable vulnerable group, youth who changed groups were most likely to move to the complete mental health group (46%) by Time 2. Similarly, of the symptomatic but content group, the majority (43%) who shifted mental health groups were classified in the complete mental health group at Time 2. Across mental health groups at Time 1, few adolescents showed declines in mental health status at Time 2 (i.e., 1% to 12% moved to the troubled group). Among students reporting psychopathology (i.e., troubled or symptomatic but content), students who also reported high well-being were more likely to move to show improvement in functioning and to move to the complete mental health class (Kelly et al., 2012).

McMahan (2012) further investigated the one-year stability of dual-factor mental health among high school students. Drawing upon the classification approach used by Suldo and Shaffer (2008), McMahan (2012) used a combination of norm-driven and sample driven cut-point criteria to classify youth. The four mental health groups defined at both Time 1 and Time 2, one year later, were: complete mental health (63%, 64%, respectively), vulnerable (11%, 12%), symptomatic but content (11%, 12%), and troubled (14%, 11%). Consistent with Kelly et al.'s (2012) findings, McMahan (2012) identified adolescents in the complete mental health group to exhibit the greatest stability over time (80%), followed by the troubled group (36%), and the vulnerable group (27%). Contrary to Kelly et al.'s (2012) research, McMahan (2012) found that youth in the symptomatic but content group exhibited the lowest levels of stability, with only 17% of students classified in this group at Time 1 remaining in the same group at Time 2. Overall, most adolescents (61%) remained in the same mental health group one year later, with 16% of adolescents exhibiting change only in levels of psychopathology and 14% exhibiting changes only in their levels of well-being. Only 9% of adolescents exhibited changes in their levels of both psychopathology and subjective well-being.

Most recently, Compton (2016) examined the stability of dual-factor metal health among early elementary aged students in kindergarten through second grade via information provided by teacher report. Compton (2016) used both a dichotomous, group-based classification scheme, as in the Kelly et al. (2012) and McMahan (2012) studies that used student self-report information, and longitudinal group-based trajectory modeling. Of the four groups defined at Time 1 and Time 2, 71% remained in the same mental health group seven months later. Of those individuals who changed groups, 13% exhibited changes in psychopathology only, 11% exhibited changes in their well-being only, and 5% showed changes in both their levels of psychopathology and well-being (Compton, 2016). The complete mental health group exhibited the greatest stability over the seven-month period, with 86% remaining in this group from Time 1 to Time 2, followed by the troubled group (61%). The symptomatic but content group exhibited moderate stability, with 44% of students remaining in this group at Time 2, with most of those who changed groups showing a decrease in psychopathology and moving to the complete mental health group. Contrary to McMahan’s (2012) but consistent with Kelly’s et al. (2012) findings, the vulnerable group exhibited the least stability, with only 24% of students remaining in this group at Time 2. Most of those who were no longer in the vulnerable group at Time 2 (51%) exhibited an increase in well-being and moved to the complete mental health group.

Recognizing limitations with group-based stability estimates formed via rationally determined cut points that do not acknowledge the continuous nature of obtained mental health data, Compton (2016) also used longitudinal trajectory modeling to examine the patterns in the stability of dual-factor mental health over four time points within 18 months. In this analysis, Compton (2016) maintained the continuous nature of the interaction between youths' well-being and psychopathology. Creating one score reflective of standardized well-being and psychopathology, five trajectory groups were evident: persistently troubled (stable low mental health scores over time; 7%), improving (low mental health scores that increased over time; 11%), declining (moderately low mental health scores that decreased over time; 9%), persistently moderate (stable moderate mental health scores over time; 39%), and persistently flourishing (stable high mental health scores over time; 34%). Thus, most early-elementary-aged individuals were found to experience flourishing or moderate mental health over a period of 18 months, with fewer youth represented in a declining or increasing mental health trajectory.

Overall, the results of previous longitudinal research suggest that dual-factor mental health groups exhibit moderate stability, with the majority (61% - 71%) of youth remaining in the same mental health group after at most one year. Youth who exhibited patterns of complete mental health were most likely to remain mentally healthy across examinations. However, patterns of instability were evident among all groups, with either the vulnerable (Compton, 2016; Kelly et al., 2012) or symptomatic but content (McMahan, 2012) groups exhibiting the lowest levels of stability. In each longitudinal study of dual-factor mental health, youth were more likely to progress toward complete mental health than to regress toward troubled mental health over time. Although the existing longitudinal research offers an expanded understanding of dual-factor mental health, this literature is limited by the short-term longitudinal nature of each study (e.g., examining only five-month, seven-month, or one-year stability) and the classification approaches (e.g., logically derived based on cut scores) used to create groups.

## The Present Study

The current study investigated the longitudinal stability of dual-factor mental health among a high school aged adolescent sample. Data collected once per year, over three years, among two cohorts of students were used to examine the stability of dual-factor mental health groups from Grades 9 to 12. In each of the three previous studies that examined the stability of dual-factor mental health, youth were classified into mental health groups using dichotomous classification criteria determined via sample-specific or norm-referenced cut points at two time points. The proportion of youth remaining in the same group at Time 2, given their Time 1 classification, was reported. However, the cut-point approach to classification has limitations. The resulting four groups reflected the binary (i.e., high versus low) cut score method used, with proportions of youth classified into each group depending on the cut-point criteria that were applied. However, criteria are often unclear regarding where to designate cut points and the use of cut points imposes differences between groups that may not be meaningful or may result in errors in group classification (e.g., Nylund, 2007). That is, variation within groups and similarities across groups are minimized. Hence, an alternative approach to dual-factor classification, latent profile analysis (LPA) has been recommended (Kim, Dowdy, Furlong, & You, 2016; Nylund, 2007; Nylund, Bellmore, Nishina, & Graham, 2007) and was utilized to empirically identify mental health groups at each time point in the current study. After empirically identifying the emerging mental health groups in each grade year, latent transition analysis (LTA) was used to examine stability and patterns in transitions among mental health classes across the high school years. Specifically, the current study examined the following research questions:

1. How stable is adolescents' dual-factor mental health from Grade 9 through Grade 12?
2. Are there lasting effects of adolescents' early mental health status?
3. Which mental health profiles exhibit greater stability over time?
4. Are patterns in stability among mental health profiles the same across transition points?

# Method

## Participants

Participants included students attending one high school in central California during the 2013-2015 academic years. Student data were collected as part of an ongoing partnership between the researchers and the high school to investigate universal screening practices. Each year, all students were invited to participate in the universal mental health screening. An accelerated longitudinal design was used for the current study. Thus, participants included two cohorts of students: Cohort A consisting of students enrolled in ninth grade in 2013-2014, and Cohort B consisting of students enrolled in tenth grade in 2013-2014. A total of 497 students in Grade 9 (91% of those enrolled) and 466 students in Grade 10 (94% of those enrolled) participated in the universal screening in 2013-2014. Given the longitudinal nature of this study, individuals with at least two years of data across the three possible years when the survey was conducted were selected for inclusion. That is, individuals selected from Cohort A included students enrolled in ninth grade in 2013-2014 who also completed the survey in tenth grade in 2014-2015 and/or eleventh grade in 2015-2016 ($n$ = 467; 94.0%)

and individuals selected from Cohort B included students enrolled in tenth grade in 2013-2014 who also completed the survey in eleventh grade in 2014-2015 and/or twelfth grade in 2015-2016 ($n$ = 408, 87.6%). The final, combined sample included 875 students across Grades 9 ($n$ = 475), 10 ($n$ = 861), 11 ($n$ = 758), and 12 ($n$ = 306). Participants were 50.4% female, 53.5% Latinx or Hispanic, 37.5% non-Hispanic White, 5.9% Asian or Pacific Islander, 1.6% Black or African American, and 1.0% American Indian or Alaska Native. In addition, 10.3% were eligible to receive special education and related services and 49.7% of students were eligible to receive free or reduced price lunch.

**Procedure**

All students in Grades 9 through 12 were invited to participate in a universal screening survey each year for three consecutive years. Following approval by the university's Institutional Review Board, district approval, passive parental consent, and student assent, school personnel administered the student surveys to participating students in a group format during one period of their regular school day. To ensure fidelity of survey administration across classrooms each year, administration scripts were provided to all classroom teachers. Data were collected within the first month of the fall semester of each of the 2013-2014 (Year 1), 2014-2015 (Year 2), and 2015-2016 (Year 3) academic years. Year 1 and 3 survey administration was completed electronically using an online survey system (i.e., SurveyMonkey and Qualtrics) whereas Year 2 administration was completed via paper-and-pencil at the request of the school administration. Previous research suggests that paper-and-pencil and online surveys completed within school settings yield generally equivalent results (e.g., Eaton et al., 2010; Hohwü et al., 2013). Students who were absent on their classroom's initial screening day were provided with up to five additional opportunities to complete the survey within two weeks of initial data collection each year.

## Measures

**Well-being indicators.** The SEHS-S is designed to measure positive psychological dispositions among students in middle and high school (Furlong, You, Renshaw, Smith, & O'Malley, 2014b; You et al., 2014). Three items measure each of 12 positive psychological traits (e.g., self-efficacy, peer support, empathy, and gratitude) that contribute to four second-order positive mental health domains that were used as indicators of well-being in this study. The four domains include: *belief-in-self* (self-efficacy, self-awareness, persistence), *belief-in-others* (school support, peer support, family coherence), *emotional competence* (emotional regulation, empathy, self-control), and *engaged living* (optimism, gratitude, zest; Furlong et al., 2014b; You et al., 2014). A five-point response scale is used on the gratitude and zest subscales (1 = *not at all*, 2 = *very little*, 3 = *somewhat*, 4 = *quite a lot*, 5 = *extremely*) whereas a four-point response scale is used for the other 10 subscales (1 = *not at all true of me*, 2 = *a little true of me*, 3 = *pretty much true of me*, 4 = *very much true of me*). Mean scores for the nine items contributing to the four second-order mental health domains (*belief-in-self*, *belief-in-others*, *emotional competence*, and *engaged living*) were used as indicators of well-being. In the Year 3 survey, one item ("I understand why I do what I do") on the *self-awareness* subscale of the *belief-in-self* domain was missing for all students. Given moderate significant correlations between items on the *self-awareness* subscale and the *belief-in-self* domain at each time point ($r$ = .22 to .50), the mean *belief-in-self* score was computed without this item for Year 3 (Grade 11 for Cohort 1, Grade 12 for Cohort 2). In the current study, internal consistency reliability estimates ranged from .80 (Grade 9) to .82 (Grade 12) for *belief-in-*

*self*, .80 (Grade 9) to .86 (Grade 12) for *belief-in-others*, .79 (Grade 9) to .85 (Grade 12) for *emotional competence*, and .87 (Grade 9) to .89 (Grade 11) for *engaged living*.

**Distress indicators.** The SDQ is a self-report measure designed to assess behavioral and emotional attributes in youth aged 4 to 17 years (Goodman, 1997, 1999). With the goal of efficiency in screening, select items from the SDQ were used as indicators of externalizing and internalizing distress. A three-factor structure including *emotional distress/withdrawal, behavioral reactivity/conduct problems*, and *prosocial behaviors/peer competence* (Dickey & Blumberg, 2004; Ruchkin et al., 2008) has been found to have superior reliability estimates with youth in the United States than the original five-factor model, consisting of *emotional symptoms*, *conduct problems*, *hyperactivity/inattention*, *peer relationship problems*, and *prosocial behavior* (Goodman 1997, 1999). The five highest loading items supported in the Ruchkin et al. (2008) three-factor model were used for each of the *emotional distress/withdrawal* (items 3, 6, 8, 13, and 16; $\lambda$ = .47 to .60) and the *behavioral reactivity/conduct problems* factors (items 2, 5, 10, 15, and 22; $\lambda$ = .56 to .62). The *emotional distress/withdrawal* items were used to measure internalizing distress whereas the *behavioral reactivity/conduct problem* items were used as a measure of externalizing distress. Factor analyses conducted on the administered SDQ items supported a two-factor model comprised of nine items: five measuring internalizing problems and four measuring externalizing problems (item 5 was removed; Moore, Dowdy, Nylund-Gibson, & Furlong, 2017). Mean scores for the internalizing (i.e., *emotional distress*) and externalizing (i.e., *behavioral reactivity/conduct problems*) distress items were computed for use in the current study. Cronbach’s alpha indicated adequate internal consistency reliability estimates for each of the internalizing (.71 in Grade 9 to .78 in Grade 12) and externalizing (.61 in Grade 9 to .72 in Grade 12) composites.

**Data Analytic Strategy**

Recognizing the limitations in current classification methods that use a cut score approach, the current study examined dual-factor mental health across Grades 9, 10, 11, and 12 using an empirical, person-centered classification scheme, LPA. A longitudinal extension of LPA, LTA (Chung, Park & Lanza, 2005; Graham, Collins, Wugalter, Chung, & Hansen, 1991) was subsequently performed to examine the stability of dual-factor mental health across the high school years. LTA is a type of structural equation model that enables the examination and description of change in latent categorical variables (e.g., mental health group) over time. As such, both measurement (i.e., LPA models at each time point) and structural (i.e., an autoregressive relation between latent class variables at each time point) model components are specified. The primary parameters of interest in LTA are transition probabilities. Transition probabilities are a type of conditional probability that indicate the likelihood of an individual being in class *k* at time point *t* given that the individual was in latent class *x* at time point *t-1* (Nylund, 2007). For example, transition probabilities provide information regarding the likelihood of an individual who is a member of Class 1 at Time 1 shifting to Class 2 at Time 2, the likelihood of individuals remaining in Class 1 at Time 2, and so on. Transition probabilities were examined to assess the degree of stability of dual-factor mental health over time.

The model building process for LTA includes examination of the cross-sectional measurement models followed by various structural specifications of the longitudinal regression model (e.g., stationary transitions, second-order effects, specification of covariates; Nylund, 2007). LTA models include multiple latent class variables from multiple time points; in the current study, four latent class variables were obtained from measurement models for the four grade years (i.e., Grades 9, 10, 11, 12). Given the accelerated longitudinal design of the current study, data were missing for all participants in Cohort A in Grade 12 and for Cohort B in Grade 9. However, all analyses were conducted using Full Information Maximum Likelihood (FIML; Enders & Bandalos, 2001) estimation using the expectation-maximization (EM) algorithm (Dempster, Laird, & Rubin, 1977), which accounts for indicator-level and longitudinal-level missingness. A cohort covariate was included in the LTA analyses to account for data that were missing by design (Little, 2011). Using FIML and the EM algorithm, latent class membership was estimated for members of Cohort A in Grade 12 and Cohort B in Grade 9.

When specifying the LTA models, the latent class variable (*c*) for each cross-sectional measurement model is regressed onto the latent class variable from the previous time point (e.g., Grade 10 latent class "*c10*" is regressed onto Grade 9 latent class "*c9*"). In doing so, the latent classes for each measurement time point become conditioned, given their direct relation to latent variables at other time points. As has been seen in cross-sectional mixture models, when structural features are jointly estimated, the addition of structural features can qualitatively change the patterns observed in emerging latent classes at each time point in unintended ways and obscure their interpretation (Asparouhov & Muthén, 2013; Vermunt, 2010). Therefore, a three-step method was used to specify the unconditional LTA and in the structural model building process in the current study to prevent changes in emerging dual-factor mental health classes at each grade year (Asparouhov & Muthén, 2013; Nylund-Gibson, Grimm, Quirk, & Furlong, 2014). Using the three-step method throughout the LTA model building process allowed for class-sizes and proportions to remain unchanged for each part of the measurement model when the structural parameters were included (i.e., the measurement parameters were fixed). Therefore, the steps used to build the LTA model in the current investigation differ from other LTA investigations that did not use the three-step approach (e.g., Nylund, 2007). The steps used included (a) explore measurement model for each time point, (b) explore measurement invariance, (c) explore structural LTA model specifications, and (d) specify the final LTA model. A description of the model building process is embedded with the results presented below. All models were estimated using M*plus* version 7.4 (Muthén & Muthén, 1998-2015).

***Determining model fit.*** A combination of indicators, including statistical indicators and substantive theory, were used in determining fit of the LPA and LTA models (Masyn, 2013; Muthén, 2003). Statistical indicators include evaluations of relative fit which assess fit of the current model by comparing it to an alternative model that differs in the number of latent classes by 1. Examples include Bayesian Information Criteria (BIC; Schwartz, 1978), adjusted BIC (ABIC), Bayes Factor (BF), correct model probability (cmP), Bootstrap Likelihood ratio Test (BLRT; McLachlan & Peel, 2000), and Vuong Lo Mendel Rubin LRT (VLMR-LRT; Vuong, 1989). Lower BIC values indicate superior fit, nonsignificant BLRT and VLMR-LRT values offer support for the *k-1* class solution, larger cmP values indicate a greater probability of the model being correct, and BF values greater than 10 offer strong evidence for a model (Masyn, 2013). Simulation studies have found that the most reliable estimates of model fit are provided by the BIC and BLRT indices (Nylund, Asparouhov, & Muthén, 2007), thus these fit indices are given the most weight. When comparing fit of LTA models with various structural specifications, a log likelihood ratio chi-square test (LRT) was used to assess if significant differences exist in fit between the two models (Nylund, 2007; Masyn, 2013).

## Results

The results are presented methodically to represent the four primary LTA modeling steps used in the current study: step 1, cross-sectional LPAs exploring the explore measurement model for each grade; step 2, examination of measurement invariance across the four measurement models; step 3, exploration of structural LTA model specifications (conditional model, second-order effects, and stationary transition probabilities); and step 4, specification of the final LTA model based on information gained in each of steps 1 through 3. An explanation of the analytic process involved at each step is included prior to discussion of the associated results.

### Step 1: Exploration of Measurement Model for Each Grade

The first step in LTA model specification involves exploration of the measurement model that will be used at each time point. Therefore, LPA models for dual-factor mental health were independently specified for Grades 9, 10, 11, and 12 using four positive mental health domains (*belief-in-self* [BIS], *belief-in-others* [BIO], *engaged living* [EL], *emotional competence* [EC]) and two psychological distress domains (*internalizing risk* [INT] and *externalizing risk* [EXT]) as indicators. Both class-invariant (i.e., item variances are freely estimated but constrained to be equal across classes) diagonal (i.e., no within class indicator covariances) and class-varying (i.e., item variance are freely estimated for each class) diagonal LPA models were examined (Kam, Morin, Meyer, & Topolntsky, 2016; Masyn, 2013; Morin et al., 2011). Missing item-level responses on each indicator were examined prior to computing composites. Mean scores were computed for individuals who answered at least 75% of items on a given composite. A model for each of Grades 9, 10, 11, and 12 was selected as the optimal model according to the statistical criterion described above and substantive dual-factor theory. The final unconditional latent class models serve as the measurement portion of the LTA model.

**Descriptive statistics.** Prior to specifying cross-sectional LPAs for each time point, descriptive information was examined for the overall sample and for each of Cohort A and Cohort B. Average responses on the mental health indicators for the whole sample as well as for each cohort are presented in Table 2. Independent samples *t* tests of the six indicators were performed to investigate whether differences existed among the two participating cohorts of students. Results indicated differences among the two cohorts primarily in Grade 10, with Cohort A having significantly higher self-reported levels of *belief-in-self*, *belief-in-others,* and *emotional competence* and lower levels of *internalizing* and *externalizing distress* ($p < .01$) than Cohort B. In Grade 11, Cohort A had significantly lower self-reported *externalizing distress* than did Cohort B ($p < .01$). A cohort covariate was included in the LTA analyses both to account for cohort level missing data as well as to control for any possible cohort effects.

**Cross-sectional LPA measurement models.** Cross-sectional LPAs were run for each of Grades 9, 10, 11, and 12. Class enumeration began with a one-class solution, followed by exploration of additional models with more latent classes. Table 3 presents the information used to evaluate the fit of each LPA model of both the class-invariant diagonal and class-varying diagonal solutions for each grade level. Fit indices produced for the Grade 9 class-invariant diagonal models support a four-class solution as the optimal LPA model (BIC = 3754.55, $p_{\text{LMRT}} = .40$ for the comparison of the five-class with the four-class solution, meaning that the addition of a fifth class does not significantly improve model fit). Although the BIC does not reach an absolute minimum at four classes, a relative leveling off occurs after the four-class model. A four-class solution was also supported in the Grade 9 class-varying diagonal solution (BIC = 3750.57, cmP = .69, $p_{\text{LMRT}}$ = .24 for the comparison of the five-class with the four-class solution); however, 17% of the log likelihood starting values did not converge, indicating instability in the model solution. This pattern held true for each of the Grade 10, 11, and 12 class-varying diagonal solutions, with between 13% and 99% of log likelihood values not converging for three- to five- class class-varying diagonal models. Therefore, the four-class, class-invariant diagonal solution was selected as the optimal LPA model for Grade 9 and only results of class-invariant diagonal solutions are discussed for the Grade 10, 11, and 12 models.

Of the Grade 10 solutions, support was offered for each of a three- (BIC = .6888.33, *p* of LMRT = <.001) and four- class solution (BIC = 6815.45). Although the BIC began approaching a relative minimum at the three-class solution (i.e., leveling off), the value of the BIC was lower in the four-class solution and exhibited minimal decreases after the four-class solution. Given recommendations for consistency in LTA measurement models (e.g., Lanza, Flaherty, & Collins, 2003) and being mindful of the goals of the larger study, we further examined the four-class solution. The estimated mean plots for the four-class solution indicated the fourth class to meaningfully differ from the other three classes. Moreover, the four emerging latent profiles were consistent with the four-class solution produced in the Grade 9 analyses. Therefore, after consideration of model fit information, substantive theory, and recommendations for specification of LTA models, the four-class class-invariant diagonal solution was selected as the optimal model for Grade 10 (Muthén, 2003).

LPA analyses in Grade 11 resulted in BIC values supporting three- to five- class solutions ($BIC_3$ = 5894.33, $BIC_4$ = 5801.09, $BIC_5$ = 5705.70). The $p_{LMRT}$ supported a five-class solution. Examination of the estimated mean plots for each solution indicated the emerging fourth class to offer substantive meaning over a three-class solution, with the four emerging classes in the four-class solution being consistent with the four emerging classes in the Grade 9 and Grade 10 solutions. In the five-class solution, the fifth emerging class appeared to represent differentiation of a class in the four-class solution fitting a pattern of average well-being and average distress that comprised approximately 29% of the sample. The differentiation resulted in two classes that displayed the following mean patterns: average to above average well-being and above average internalizing distress (12%) and average well-being and low-average distress (17%). Despite slight differences on the well-being and distress indicators, the additional class offered little additional substantive meaning considering existing dual-factor or two-continua research. In addition, given the complexity of the modeling specifications for LTA, preference exists for parsimonious cross-sectional solutions that offer longitudinal consistency, when appropriate, across data points (e.g., Lanza et al., 2003). As the four-class solution produced in the Grade 11 solution paralleled the four-class solutions in the Grade 9 and 10 analyses, a four-class solution was selected as the optimal model for Grade 11 (Muthén, 2003).

In the Grade 12 solutions, although the BIC reached an absolute minimum in the five-class solution (2516.32), the differences in the BIC with the four- (BIC = 2519.36) and six-class (BIC = 2520.89) solutions were negligible. The BF and cmP supported a five-class solution (9.84 and .76, respectively), however, these indices are computed based upon the BIC value for each class and thus reflect the absolute minimum of the BIC in the five-class solution. The $p_{LMRT}$, which is computed independently from the BIC, supported a four-class solution ($p_{LMRT} = .42$ for the comparison of the five-class with the four-class solution, meaning that the addition of a fifth class does not significantly improve model fit). Further, examination of the estimated means plot indicated the classes emerging in the four-class solution to be substantively similar to the four classes in the Grade 9, 10, and 11 solutions. Therefore, the four-class solution was selected as the optimal model for each of Grades 9, 10, 11, and 12.

Figure 1 presents the estimated mean plots for the four-class LPA solutions. Although varying slightly in indicator means over time, the four classes maintained a substantively similar pattern across the four grade years. Based on the pattern of mean scores across the well-being and distress domains, the following labels are offered for the four emerging classes across each grade: *complete mental health* (high well-being and low distress), *moderately mentally healthy* (high-average well-being and low distress), *symptomatic but content* (average to high-average well-being and average to above-average distress), and *troubled* (average to low-average well-being and above-average distress).

**Step 2: Examining Measurement Invariance**

Given that a four-class solution was selected as the optimal model for each grade, measurement invariance constraints were explored. Traditionally, after selecting the measurement model for each time point, an unconditional LTA model is specified prior to examination of measurement invariance constraints (e.g., Lanza et al., 2003; Nylund, 2007). However, with the development of three-step procedures that control for covariation effects on emerging latent classes when structural features are added, testing measurement invariance prior to specifying the latent regression paths between the grade-specific latent class variables (i.e., the unconditional LTA model) is preferred for maintaining the features of the measurement model when the LTA model is specified. As a result, unique to the three-step modeling approach, measurement invariance was examined prior to including the latent regression paths of a LTA model in the current study (i.e., the four measurement models were specified simultaneously, but autoregressive relations between each latent class "*c*" variables were not included).

Three measurement invariance specifications can be explored when examining multiple measurement models with the same number of emerging latent classes, including full measurement invariance, partial measurement invariance, and full measurement noninvariance (Nylund, 2007), with the measurement parameters of interest in the current study being the class-specific indicator means for each cross-sectional LPA model. In the current study, measurement invariance was examined by specifying (a) a model assuming full measurement non-invariance, such that all parameters were freely estimated and allowed to vary across each grade; and (b) a model assuming full measurement invariance, such that all measurement parameters are constrained to be equal across time (Lanza et al., 2003). The LRT was used to assess for significant differences in model fit when the invariance constraints were specified.

The model assuming full non-invariance exhibited improved fit over the model assuming full invariance, $\chi^2_{diff}(72) = 310.15$, $p < .001$. However, this result was expected given the large number of parameters that were constrained to be equal in the full invariance solution, thus increasing the degree of model misfit. As can be seen in the Figure 1, means plots of the mental health profiles are similar across grades, providing evidence that measurement invariance could reasonably be assumed. Moreover, assuming measurement invariance is recommended when the same number and type of classes emerges across measurement time points, which is the case in this study. When measurement parameters are held equal at each time point, changes in mental health group membership are directly interpretable as related to developmental changes occurring over time rather than due to relations between the mental health indicators with each class (Lanza et al., 2003); that is, assuming measurement invariance allows for clearer interpretation of the transition probabilities of interest in the current study (Nylund, 2007). Therefore, the unconditional full measurement invariance model was selected for the following analyses.

**Step 3: Exploration of Structural Model Specifications**

Following examination of measurement invariance, the LTA model was specified to include full measurement invariance and to examine stability and transitions among mental health classes from Grade 9 to Grade 10, Grade 10 to Grade 11, and Grade 11 to Grade 12. Cohort was controlled for in the LTA model building process by specifying a cohort covariate regressed onto each transition point. Therefore, the observed transition probabilities reflect stability in dual-factor mental health classes after controlling for any cohort effects. After specification of the initial LTA model controlling for cohort effects and assuming full measurement invariance, additional structural model specifications were explored (i.e., stationary transition probabilities, second-order effects).

**Examination of transition probabilities.** First, we examined whether the transition probabilities were equal across the three transition periods (i.e., Grade 9 to Grade 10, Grade 10 to Grade 11, and Grade 11 to 12). Stationary transitions would indicate that the probability of changing mental health classes is equal for each transition point across transition periods (e.g., probability of moving from Grade 9 class 1 to Grade 10 class 2 is equal to the probability of moving from Grade 10 class 1 to Grade 11 class 2). When assuming stationary transitions, transition probabilities are constrained to be equal. In the current study, two LTA models were fit to examine whether assuming stationarity in transitions improves model fit. The first model, the LTA model assuming full measurement invariance, estimated a transition probability matrix for each transition between grades. The second model, building upon the first LTA model, constrained the transition probabilities to be equal across the three transition periods. It is important to note that when covariates are considered, the stationarity assumption is not appropriate (Nylund, 2007). However, given interests in examining whether changes in dual-factor mental health vary as a function of developmental time, we examined the stationarity assumption without the cohort covariate effect. Results of the LRT comparing the two models indicated a significant worsening in fit when holding the transition probabilities constant, $\chi^2_{diff}(24) = 108.04$, $p < .001$. Therefore, students' probability of transitioning among the dual-factor mental health classes varied throughout high school and stationary transitions are not assumed in the models with additional structural specifications described below.

**Second-order effects.** Given the interest in examining stability of dual-factor mental health beyond a one-year period, second-order effects were also examined. A second-order effect implies a lasting effect of mental health status, for example, whether Grade 9 mental health predicts Grade 11 mental health above and beyond the indirect relation of Grade 11 mental health with Grade 9 mental health via Grade 10 mental health class membership. Similar to the process for investigating whether stationary transitions were appropriate, when testing for second-order effects, two LTA models were run: the first specifying only first-order comparisons (i.e., Grade 9 to Grade 10, Grade 10 to Grade 11, Grade 11 to Grade 12) and the second including the second-order effects of mental health in Grade 11 with Grade 9 and Grade 12 with Grade 10. Each controlled for the cohort covariate. Results indicated that the second-order transition model significantly improved fit, $\chi^2_{diff}(18) = 30.24$, $p = .022$, which suggests that there is a lasting effect of students dual-factor mental health in Grade 9 and Grade 10 that affects their mental health in Grade 11 and 12, respectively.

**Step 4: Specification of the Final LTA Model**

Given the results of the LTA model building process described above, the final LTA model was specified to control for a cohort covariate effect and to include full measurement invariance, nonstationary transitions, and second-order effects between Grades 9 and 11 and Grades 10 and 12. Table 4 presents the class proportions for each grade year after specification of the final conditional LTA model. The proportion of students classified into the *complete mental health* class grew from Grade 9 (19%) to Grade 12 (36%) whereas the proportion of students in the *moderately mentally healthy* class decreased from Grade 9 (50%) to Grade 12 (33%). The size of the *symptomatic but content* class was relatively consistent, with the smallest percentage of students classified into this class in Grade 10 (19%). Finally, the size of the *troubled* class grew from Grade 9 (3%) to Grade 10 (7%), but then remained consistent until Grade 12 (7%).

Table 5 displays the transition probabilities for the first-order effects of the final LTA model. Overall, one-year stability in dual-factor mental health membership was the strongest from Grade 9 to Grade 10. For example, of students who were most likely to be classified into the *complete mental health* class in Grade 9, 79% remained in the *complete mental health* class in Grade 10. Similarly, 70% of students in the *moderately mentally healthy* class in Grade 9 remained in this class in Grade 10. The lowest levels of stability were evident for the *symptomatic but content* class, with 46% of students in this class in Grade 9 remaining in the class in Grade 10. The *complete mental health* class exhibited the highest levels of stability across two transition points (i.e., Grade 9 to 10 and Grade 11 to 12), whereas the *troubled* class exhibited the least stability across two transition points (i.e., Grade 10 to 11 and Grade 11 to 12). Overall, the Grade 11 to 12 comparison demonstrated the lowest levels of stability across each of the *moderately mentally healthy*, *symptomatic but content*, and *troubled* mental health groups, with less than 35% of participants classified in each class in Grade 11 remaining within the same class in Grade 12. Looking across the three one-year transition points (i.e., Grades 9 to 10, 10 to 11, and 11 to 12), the *complete mental health* class had the greatest average stability (77%), followed by the *moderately mentally healthy* class (56%), the *symptomatic but content* class (47%), and the *troubled* class (42%).

Of those students who exhibited instability across the one-year comparisons (see Table 5), students initially fitting a *complete mental health* profile were, on average, most likely to transition to the *moderately mentally healthy* class followed by the *symptomatic but content* class. Students fitting a *moderately mentally healthy* profile were, on average, similarly likely to transition into the *complete mental health* class (22%) or the *symptomatic but content* class (20%). Of those in a *symptomatic but content* class, students were, on average, more likely to transition into a *moderately mentally healthy* class (37%), followed by a *troubled* class (14%). Of those students who transitioned out of a *troubled* class, most transitioned into a *symptomatic but content* class followed by a *moderately mentally healthy* class. It was very unlikely for students to transition from the *complete mental health class* to the *troubled* class over a one-year period. Thus, students were more likely to transition into a healthier mental health class (i.e., characteristic of average- to above-average strengths and low to average distress) than into a less healthy class (i.e., characteristic of low-average strengths and average to above-average distress).

The second-order effects comparing two-year transitions from Grade 9 to Grade 11 and from Grade 10 to Grade 12 are indicative of similar patterns. Table 6 presents the transition probabilities for the second-order effects, while controlling for cohort-effects. Similar to the one-year comparisons, when comparing dual-factor mental health stability over two years, the *complete mental health* group exhibited the most stability (69%). The *symptomatic but content* class exhibited the second greatest stability (56%), followed by the *moderately mentally healthy* (52%) and *troubled* (36%) classes. Stability estimates for each class were similar across both two-year comparisons, with the *troubled* class showing stronger two-year stability from Grade 10 to 12 than from Grade 9 to 11.

With four classes across four time points, 256 ($4^4$) transition patterns were possible based upon the estimated model. Of these possible patterns, 116 were observed. Twenty-five patterns were followed by 10 or more participants and comprised 78.2% of the sample. The patterns comprising the largest proportion of the sample were individuals who remained in the *complete mental health* (10.4%) and *moderately mentally healthy* (9.5%) classes across each of Grades 9, 10, 11, and 12. Approximately 3.7% of participants remained in the *symptomatic but content* class across each grade year, whereas only 0.4% of participants remained in the *troubled* class over the four years. Therefore, most students changed mental health class at least once over the four years. However, 42.3% of students were in either the complete mental health or moderately mentally healthy classes over each of the four years whereas 10.6% were in either the symptomatic but content or troubled classes over each of the four years. Figure 2 summarizes the four-year stability patterns for each of the *complete* *mental health*, *moderately mentally healthy*, *symptomatic but content*, and *troubled* groups based on the final estimated LTA model.

## Discussion

Although mental health models describing the intersection of well-being and distress are increasingly recognized and empirically supported (e.g., Greenspoon & Saklofske, 2001; Suldo & Shaffer, 2008), a majority of the research into these dual-factor models of mental health has been cross-sectional. No research to date has examined the stability of dual-factor mental health over a period longer than one year within an adolescent population. Therefore, the current study contributed to the literature by examining the stability of adolescents' dual-factor mental health across the high school years. Specifically, this study used LTA to model transition patterns among emerging latent mental health groups across Grades 9 through 12, as well as probabilities of transitioning from, or remaining within, a group. Prior to specifying the longitudinal LTA models, cross-sectional LPA measurement models were tested for each of Grades 9 through 12. Four mental health classes emerged across each grade year: *complete mental health* (high well-being and low distress), *moderately mentally healthy* (high-average well-being and low distress), *symptomatic but content* (average to high-average well-being and average to above-average distress), and *troubled* (average to low-average well-being and above average distress). Contrary to previous dual-factor research, a vulnerable or languishing group (i.e., low well-being and low distress) did not emerge when dual-factor mental health groups were formed via LPA rather than via rationally determined cut points.

**Stability of Dual-Factor Mental Health**

Through a LTA model building process using a three-step method, a final LTA model was selected that held measurement parameters equal across the four grade years and included first-order transitions among Grades 9 to 10, 10 to 11, and 11 to 12 as well as second-order transitions among Grades 9 to 11 and 10 to 12. The LTA model including second-order effects fit significantly better than a model that included only first-order effects, supporting a lasting impact of one's current dual-factor mental health status and indicating that current dual-factor mental health predicts mental health status two years later above and beyond an indirect relation between mental health status in the intermediate year. The resulting LTA transition patterns across Grades 9 through 12 indicated that between 0.4% (*troubled*) and 10% (*complete mental health*) of students were classified into the same mental health class across the four-year period, with the strongest four-year stability observed for students in the most-healthy *complete mental health* (10%) and *moderately mentally healthy* (9%) classes who reported average to above average well-being and low distress. These results parallel Compton's (2016) investigation of 18-month longitudinal trajectories of dual-factor mental health. Similar to Compton's results, students experiencing persistent *complete mental health* and *moderate mental health* across the four years comprised the largest observed transition patterns. Youth fitting a persistently *troubled* pattern comprised the smallest stability pattern.

In previous research that examined the stability of dual-factor mental health across two time points within one year, most students were found to remain in the same mental health group over time (61% to 71%; Compton, 2016; Kelly et al., 2012; McMahan, 2012). Similarly, when examining transitions among two time points across one and two years in the current study, a majority remained in the same mental health class (55%). In the previous longitudinal examinations, the *complete mental health* group was found to demonstrate the greatest stability (86%, Compton, 2016; 85%, Kelly et al., 2012; 80%, McMahan, 2012) followed by the *troubled* group (61%, Compton, 2016; 47%, Kelly et al., 2012; 36%, McMahan, 2012). In comparison, the *symptomatic but content* (17%, McMahan, 2012) or *vulnerable* (44%, Compton, 2016; 42%, Kelly et al., 2012) groups were found to have the least stability. Congruent with previous research, the *complete mental health* class exhibited the greatest stability, on average, across comparison points in the current study (73%). Greater stability was observed across one-year comparisons (77%) than across the two-year comparisons (69%).

Contrary to previous research, the *troubled* class demonstrated the least stability (39%) as compared to the other emerging mental health groups in the current study. Of students initially classified into a troubled class, 42% remained in this class one year later, and 36% remained two years later. The *troubled* group similarly had the poorest four-year stability, with less than 1% of students classified in the *troubled* class in Grade 9 remaining in that class in Grades 10, 11 and 12. Although the rank ordering of average stability estimates among groups differs from previous research, the proportion of youth who remained in the *troubled* group across one-year periods in the current study (25% from Grade 11 to 12, 40% from Grade 10 to 11, and 60% from Grade 9 to 10), is consistent with previous research examining stability over one year or less with middle school students (47%; Kelly et al., 2012), high school students (36%; McMahan, 2012), and early elementary school students (61%; Compton, 2016). In addition, whereas McMahan (2012) found a *symptomatic but content* group to have the least stability for high school students over one year (17%), the *symptomatic but content* class in the current study exhibited moderate stability (52%) over one- (47%) and two-year (56%) comparisons. These results are consistent with estimates produced for early elementary (Compton, 2016) and middle-school (Kelly et al., 2012) students. The disparities in stability estimates among adolescents in the *troubled* and *symptomatic but content* groups in this study may reflect differences in measurement tools (e.g., a screening instrument was used to assess distress in the current study, whereas previous research has tended to use more comprehensive clinical measures) or classification method (i.e., empirical versus cut-score approaches). Overall, in the current study, greater stability was observed for adolescents in mental health classes characteristic of average to above-average well-being (i.e., *complete mental health* [73%], *moderately mentally healthy* [54%], and *symptomatic but content* [52%]) than the *troubled* class (39%) who reported the lowest average levels of well-being.

Among students who transitioned classes across comparison points in the current study, students were more likely to transition into a more flourishing well-being class than into a class with lower levels of well-being and greater levels of distress. For example, among those experiencing distress (*symptomatic but content* and *troubled*), students were more likely to show an improvement in their levels of well-being and distress over time. Consistent with the three previous longitudinal studies, students in the present study also demonstrated a trend toward moderate or complete mental health over time. Fewer than 5% of youth remained in the *troubled* and in the *symptomatic but content* classes across all grade years, suggesting that adolescents who report experiencing distress with limited well-being at the beginning of high school are unlikely to remain in this mental health state for the entirety of their high school experience. However, of the 25% to 35% of students experiencing distress in one grade, less than 8% were likely to transition into a *complete mental health* group over a one-year period, with fewer than 22% transitioning to a *complete mental health* group after two years. Students exhibiting *symptomatic but content* profiles were more likely to achieve *a complete mental health* status one to two years later than those fitting a *troubled* profile. Overall, these results highlight the chronicity of distress in conjunction with average to low-average strengths (Compton, 2016; McMahan, 2012) as well as the need for intervention particularly with these youth. In contrast, students who were in the *complete mental health* class were most likely to remain in this class or to enter the *moderately mentally healthy* class.

Although general trends can be observed across the multiple comparison points available in the current study, it is important to note that variability was evident, particularly across the one-year comparisons. For example, stability estimates over one year ranged from 61% (Grade 10 to 11) to 93% (Grade 11 to 12) for *complete mental health*, 34% (Grade 11 to 12) to 70% (Grade 9 to 10) for *moderately mentally healthy*, 26% (Grade 11 to 12) to 69% (Grade 10 to 11) for *symptomatic but content*, and 25% (Grade 11 to 12) to 60% (Grade 9 to 10) for *troubled*. Whereas stability from Grade 11 to 12 was lowest for the *moderately mentally healthy*, *symptomatic but content*, and *troubled* classes, stability for *complete mental health* was strongest across these two grades. Stability estimates similarly demonstrated variability across two-year comparisons. This observed variability combined with the statistically demonstrated inappropriateness of an equality assumption across transition points (i.e., stationary transitions) indicated that the rate of change in dual-factor mental health varies across high school grades. This finding is noteworthy as it highlights important limitations to previous longitudinal work in which dual-factor mental health group membership was examined only across two time points or within up to a one-year period. Although contributing greatly to the growing understanding of dual-factor mental health, caution is recommended in generalizing from the stability estimates provided in previous short-term longitudinal work examining only two time periods. Given the variability observed between comparison points in the current study, the stability estimates provided in previous research may also reflect age-specific information that may differ for youth at other age or grade levels. Additional longitudinal research is needed to replicate the results of the current and previous research, and to expand both the time frame for measurement and age levels of participants. Moreover, research examining individual or contextual characteristics associated with transition patterns (i.e., the influence of covariates on transition probabilities) can provide additional information important in understanding patterns in instability (e.g., why some students in a *troubled* class transition to a *symptomatic but content* class whereas other transition to a *moderately mentally healthy* class) which may then further inform intervention recommendations.

**Implications for School-Based Mental Health Practice**

The results of the current study offer continued support for the expanded, dual-factor conceptualization of mental health. At each grade level, variation was observed across levels of well-being and distress, resulting in four emerging LPA identified mental health groups that differed along both well-being and distress dimensions. The observed patterns of the four emerging groups (Figure 1), particularly the presence of a *symptomatic but content* group demonstrating average levels of both well-being and distress, indicate that the traditional, bipolar view of mental health is insufficient for describing youths' mental health experiences and in informing comprehensive assessment, prevention, and intervention. Whereas problem-focused interventions are intended only for those students experiencing the most distress (e.g., *troubled* group; e.g., Suldo & Shaffer, 2008), interventions designed within a dual-factor framework that target both distress and well-being could benefit all students (Furlong, Dowdy, Carnazzo, Bovery, & Kim, 2014). Moreover, within comprehensive, multitiered systems of mental health support, interventions can be implemented at each of three tiers and would benefit all students within a school (Suldo & Shaffer, 2008; Suldo et al., 2016). For example, universal wellness promotion programs can build or maintain social-emotional strengths and may serve to bolster the mental health of those in a *moderately mentally healthy* class and maintain others' *complete mental health* status. Targeted and intensive interventions would then be reserved for youth experiencing distress, aiming to ameliorate distress while supporting (i.e., for *symptomatic but content*) or building (i.e., for *troubled*) well-being (Suldo & Shaffer, 2008). Therefore, in school-based mental health efforts, interventions targeted at both wellness promotion and prevention and treatment of distress are needed.

Findings from the present study also indicate the need to regularly monitor students' mental health, with respect to both well-being and distress to accurately inform promotion, prevention, and intervention efforts. Although, on average, 73% of students within a *complete mental health* class maintained their mental health status one year later, across comparison points up to 39% (Grade 10 to 11) of students declined from their *complete mental health status* one year later, with up to 35% (Grade 9 to 11) moving from a complete mental health class across two-year comparisons. Universal screening has been recommended as one way of monitoring students' mental health need to inform prevention and early intervention efforts (Glover & Albers, 2007). Scholars supporting a dual-factor model of mental health recommend screening for individual strengths in addition to psychological distress—that is, screening for complete mental health (e.g., Dowdy et al., 2015; Furlong et al., 2014a; Moore et al., 2015). Through universal screening for complete mental health, schools can identify youth who are experiencing immediate psychological distress, as well as those who, although not in current distress, are also not thriving (Furlong et al., 2014a). In this way, information gained via screening for complete mental health can be utilized not only to identify or prevent mental illness, but also to promote positive mental health outcomes and well-being for all students.

Currently, inconsistent recommendations exist regarding the frequency with which to conduct mental health screening efforts. For example, recommendations range from screening when students enter a new school (Stoep et al., 2005), to multiple times per year (Ennis, Lane, & Oakes, 2012; Severson, Walker, Hope-Doolittle, Kratochwill, & Gresham, 2007), to once per year (Dowdy, Furlong, Eklund, Saeki, & Ritchey, 2010; Dowdy et al., 2014), to only during key developmental time periods for a given problem (Stoep et al., 2005). The longitudinal results of the current study have the potential to further inform recommendations regarding frequency of screening and assessment for complete mental health. For example, with respect to screening at entry into a new school (i.e., in Grade 9), the greatest average stability was observed among the dual-factor mental health classes from Grade 9 to 10; however, much movement occurred among the mental health classes following the Grade 9 screening assessment. On average, students in the healthiest group (i.e., *complete mental health*; high well-being, low distress) exhibited the greatest stability across comparisons, suggesting that approximately 70% of adolescents maintain positive mental health over a two-year period. However, few students (10%) remained in the *complete mental health* class across each of four years, suggesting that screening for complete mental health only once during the high school period would be insufficient. Examination of transition patterns indicated that only 24% of students remained in the same mental health class across all time points, thus, screening only once at entry into school limits a school's ability to inform intervention for students beyond the current academic year. At the very least, the results of the current study indicate the need for screening at the start of high school and in Grade 12, where stability in dual-factor mental health from the previous year was the lowest across *moderately mentally healthy*, *symptomatic but content*, and *troubled* groups. However, observed variability across stability estimates and instability patterns across the one- and two-year transition periods indicate that in order to most accurately identify and refer students for intervention, screening may need to occur at least once per year.

As the screening data used for the current study were collected at one-year intervals, our results are limited in their ability to determine if there is an added benefit of screening multiple times within an academic year versus screening only once per academic year. However, the moderate stability observed across one-year periods indicates that screening multiple times per year may be unnecessary. Continuing to assess students' mental health status after placement into an intervention within a given academic year (i.e., progress monitoring), however, is critical for informing effectiveness of intervention efforts. Overall, the results of the current study support recommendations to monitor students' dual-factor mental health once per academic year (Dowdy et al., 2010, 2014). Variability was observed in stability of mental health groups across well-being and distress profiles, however, greater stability was observed among the more flourishing groups (i.e., adolescents who were in a *complete mental health* class tended to have most stability) with youth in a *troubled* class having the least stability. Therefore, screening yearly for both well-being and distress is critical for informing referral into interventions that can ameliorate distress as well as bolster well-being. In doing so, intervention may aid students to achieve a stable, complete mental health status and prevent those with complete mental health from declining (McMahan, 2012). Additional research is needed to further inform the frequency with which to conduct universal complete mental health screening; specifically, whether screening multiple times per year offers an advantage over screening once per year.

**Limitations and Future Directions**

Despite the strengths of the current study, important limitations warrant discussion. First, given the difficulties of conducting longitudinal research, the current study used an accelerated longitudinal design including two cohorts of participants (Cohort A: Grades 9 to 11; Cohort B: Grades 10 to 12). Although allowing an examination of the stability of dual-factor mental health across the high school years, data were missing by design in Grades 9 and 12. However, because information regarding participants' dual-factor mental health was modeled using the EM algorithm that uses known information about class membership to estimate parameters for students with missing data, a cohort covariate was included in the structural LTA analyses to control for the effect of observed cohort differences on well-being and distress measurement indicators on observed structural transition probabilities. Therefore, although cohort effects were controlled for within the LTA models, the presence of cohort effects represents a limitation in the sample used for the current study. In addition, information was not available regarding whether participants received intervention following universal screening each year; thus, we are unable to identify the extent to which interventions may have impacted observed transition probabilities. Additional research that replicates the current findings within additional large samples of youth followed across all four years of high school while also controlling for intervention exposure is needed.

Additionally, although an LPA approach to classification and examination of stability of dual-factor mental health has several advantages over a rationally determined cut score approach (e.g., uses individuals' responses to mental health indicators to empirically *identify* emerging groups rather than rationally determined cut points to *define* groups; models heterogeneity among groups that would otherwise be treated as homogenous; Kim et al., 2016), LPA classification is not without its challenges. For example, a combination of empirical and substantive fit criteria is used during the class enumeration process to inform the selection of the optimal class solution that is used within the measurement models of LTA. However, as evidenced in the current study, statistical indices are not always conclusive or in agreement regarding the number of latent classes in the optimal model. Most notably, in the Grade 10 and Grade 11 LPA solutions, empirical fit criteria supported models with either three (Grade 10) or five (Grade 11) classes in addition to a four-class solution. When empirical fit criteria do not clearly indicate a single solution, using substantive theory and considering parsimony of plausible solutions is recommended in further examining the appropriateness of different solutions (Masyn, 2013). Within the current study, recommendations for consistency in the number of latent classes across grade years (e.g., Lanza et al., 2003) were also heeded to enable specification of measurement invariance constraints and thus allowing straightforward interpretation of the LTA estimated transition probabilities and patterns. However, relying upon empirical fit of independent LPA measurement models, specifying a three-class solution in Grade 10 or a five-class solution in

Grade 11 would also have been appropriate in the LTA measurement model of the present study. Thus, these results should be considered as one possible solution and as an initial step in the examination of the longitudinal stability of dual-factor mental health in adolescents using LTA. Replication of the current LPA and LTA analyses with additional, large, and diverse student samples is needed. Replication is further indicated given that the number of latent dual-factor mental health groups is empirically identified based on the observed heterogeneity within a given sample, and that the current study used data from a single high school. Therefore, the inability to identify a vulnerable or languishing class (i.e., low well-being, low distress) in the current LPA analyses may reflect sample specific characteristics such that the number of individuals fitting a vulnerable profile was too few to be detected or that a languishing group is an artifact of a rational cut point approach to classification.

Finally, the longitudinal results of the current study yielded similarities with previously conducted dual-factor stability research (i.e., Compton, 2016; Kelly et al., 2012; McMahan, 2012); however, nontrivial differences were also observed. For example, paralleling previous work, the *complete mental health* class exhibited the greatest average stability across comparison points in the current study, with most students who transitioned across comparison points trending toward *moderate* or *complete mental health*. However, students fitting a troubled mental health pattern exhibited the lowest levels of stability in the current study, whereas previous research indicated students in a *troubled* group to have the second greatest stability estimates. These differences may reflect the different classification approaches used across studies (i.e., LTA versus cut-score defined, group-based analyses), discrepancies in measurement tools used, or sample specific characteristics. Overall, additional research is needed that examines stability of dual-factor mental health, specifically whether differences in classification approaches influence stability results. Future research investigating the relation of longitudinal dual-factor mental health trajectories to distal outcomes (e.g., graduation rates, development of psychological disorder) as well as individual and school-level predictors of stability can further inform school-based prevention and early intervention efforts for all students.

## References


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

Asparouhov, T., & Muthén, B. (2013). *Auxiliary variables in mixture modeling: 3-step approaches using M*plus (pp. 1–48). Los Angeles, CA: Muthén & Muthén. Retrieved from http://www.statmodel.com/examples/webnotes/webnote15.pdf

Brock, S. E. (2015). Mental health matters. *Communiqué, 43*(7), 13–15.

Chung, H., Park, Y., & Lanza, S. T. (2005). Latent transition analysis with covariates: Pubertal timing and substance use behaviours in adolescent females. *Statistics in Medicine, 24,* 2895–2910. doi:10.1002/sim.2148

Compton, A. (2016). *Examining the longitudinal stability of a dual-factor model of mental health in early elementary school students.* Doctoral Dissertation, University of Washington. Retrieved from https://digital.lib.washington.edu/researchworks/bitstream/handle/1773/37096/Compton_washington_0250E_16391.pdf?sequence=1

Deković, M., Buist, K. L., & Reitz, E. (2004). Stability in changes in problem behavior during adolescence: Latent growth analysis. *Journal of Youth and Adolescence, 33*, 1–12. doi:10.1023/A:1027305312204

Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood from incomplete darn via the EM algorithm (with discussion). *Journal of the Royal Statistical Society, 39,* 1–38.

Dickey, W. C., & Blumberg, S. J. (2001). Revisiting the factor structure of the Strengths and Difficulties Questionnaire. *Journal of the American Academy of Child and Adolescent Psychiatry, 43*, 1159–1167. doi:10.1097/01.chi.0000132808.36708.a9

Dowdy, E., Furlong, M. J., Eklund, K., Saeki, E., & Ritchey, K. (2010). Screening for mental health and wellness: Current school-based practices and emerging possibilities. In B. Doll, W. Pfohl, & J. Yoon (Eds.), *Handbook of youth prevention science* (pp. 70–95). New York, NY: Routledge.

Dowdy, E., Furlong, M. J., Raines, T., Bovery, B., Kauffman, B., Kamphaus, R., … & Murdock, J. (2015). Enhancing school-based mental health services with a preventive and promotive approach to universal screening for complete mental health. *Journal of Educational and Psychological Consultation*, *25*, 1–20. doi:10.1080/10474412.2014.929951

Dowdy, E., Nylund-Gibson, K., Felix, E. D., Morovati, D., Carnazzo, K. W., & Dever, B. V. (2014). Long-term stability of screening for behavioral and emotional risk. *Educational and Psychological Measurement*, *74*(3), 453–472. doi:10.1177/0013164413513460

Eaton, D. K., Brener, N. D., Kann, L., Denniston, M. M., McManus, T., Kyle, T. M., … & Ross, J. G. (2010). Comparison of paper-and-pencil versus web administration of the Youth Risk Behavior Survey (YRBS): Risk behavior prevalence estimates. *Evaluation Review, 34*(2), 137–153. doi:10.1177/0193841X10362491

Eklund, K., Dowdy, E., Jones, C., & Furlong, M. J. (2011). Applicability of the dual-factor model of mental health for college students. *Journal of College Student Psychotherapy*, *25*, 79–92. doi:10.1080/87568225.2011.532677

Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal, 8,* 430–457. doi:10.1207/S15328007SEM0803_5

Ennis, R. P., Lane, K. L., & Oakes, W. P. (2012). Score reliability and validity of the student risk screening scale: A psychometrically sound, feasible tool for use in urban elementary schools. *Journal of Emotional and Behavioral Disorders, 20,* 241–259. doi:10.1177/1063426611400082

Ferdinand, R. F., Verhulst, F. C., & Wiznitzer, M. (1995). Continuity and change of self-reported problem behaviors from adolescence into young adulthood. *Journal of the American Academy of Child and Adolescent Psychiatry, 34*(5), 680–690. doi:10.1097/00004583-199505000-00020

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

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

Glover, T. A., & Albers, C. A. (2007). Considerations for evaluating universal screening assessments. *Journal of School Psychology, 45*, 117–135. doi:10.1016/j.jsp.2006.05.005

Goodman, R. (1997). The Strengths and Difficulties Questionnaire: A research note. *Child Psychology & Psychiatry & Allied Disciplines, 38*(5), 581–586. doi:10.1111/j.1469-7610.1997.tb01545.x

Goodman, R. (1999). The extended version of the Strengths and Difficulties Questionnaire as a guide to child psychiatric caseness and consequent burden. *Journal of Child Psychology, Psychiatry, and Allied Disciplines, 40,* 791–799. doi:10.1111/1469-7610.00494

Graham, J. W., Collins, L. M., Wugalter, S. E., Chung, N. K., & Hansen, W. B. (1991). Modeling transitions in latent stage-sequential processes: A substance use prevention example. *Journal of Consulting and Clinical Psychology, 59*, 48–57. doi:10.1037/0022-006X.59.1.48

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

Huebner, E. S. (2004). Research on assessment of life satisfaction of children and adolescents. *Social Indicators Research, 66*, 3–33. doi:10.1023/B:SOCI.0000007497.57754.e3

Huebner, E. S., Funk, B. A., & Gilman, R. (2000). Cross-sectional and longitudinal psychosocial correlates of adolescent life satisfaction reports. *Canadian Journal of School Psychology, 16*, 53–64. doi:10.1177/082957350001600104

Hoagwood, K., & Johnson, J. (2003). School psychology: A public health framework: 1. From evidence-based practices to evidence-based policies. *Journal of School Psychology*, *41,* 3–21. doi:10.1016/S0022-4405(02)00141-3

Howhü, L., Lyshol, H., Gissler, M., Jonsson, S. H., Petzold, M., & Obel, C. (2013). Web-based versus traditional paper questionnaires: A mixed-mode survey with a Nordic perspective. *Journal of Medical Internet Research, 15*(8), e173. doi:10.2196/jmir.2595

Jahoda, M. (1958). *Current concepts of positive mental health.* New York, NY: Basic Books.

Kam, C., Morin, A. J. S., Meyer, J. P., & Topolnytsky, L. (2016). Are commitment profiles stable and predictable? A latent transition analysis. *Journal of Management, 42*(6), 1462–1490. doi:10.1177/0149206313503010

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

Keyes, C. L. M. (2002). The mental health continuum: From languishing to flourishing in life. *Journal of Health and Social Research, 43*, 207–222. doi:10.2307/3090197

Kim, E. K., Dowdy, E., Furlong, M. J., & You, S. (2016). Mental health profiles and quality of life among Korean adolescents. *School Psychology International* (Advance Online Publication). doi:10.1177/0143034316682296

Kim, E. K., Furlong, M. J., Dowdy, E., & Felix, E. D. (2014). Exploring the relative contributions of strength and distress components of dual-factor complete mental health screening. *Canadian Journal of School Psychology, 29*(2), 127–140. doi:10.1177/0829573514529567

Lanza, S. T., Flaherty, B. P., & Collins, L. M. (2003). Latent class and latent transition analysis. *Handbook of Psychology, 4*, 663–685. doi:10.1002/0471264385.wei0226

Little, T. D. (2011). *Advances in missing data and implications for developmental science.* Presentation at the Society for Research in Child Development Biennial Meeting, Montreal, Quebec, Canada.

Masyn, K. E. (2013). Latent class analysis and finite mixture modeling. In T. D. Little (Ed.), *The Oxford handbook of quantitative methods* (pp. 551–611). New York, NY: Oxford University Press.

McLachlan, G., & Peel, D. (2000). *Finite mixture models*. New York, NY: Wiley.

McMahan, M. M. (2012). *A longitudinal examination of high school students' group membership in a dual-factor model of mental health: Stability of mental health status and predictors of change* (Doctoral Dissertation). Retrieved from University of South Florida Scholar Commons (4369).

Merikangas, K. R., Jian-ping, H., Burstein, M., Swanson, S. A., Avenevoli, S., Lihong, C., … & Swendsen, J. (2010). Lifetime prevalence of mental disorders in US adolescents: Results from the National Comorbidity Study-Adolescent Supplement (NCS-A). *Journal of the American Academy of Child and Adolescent Psychiatry, 49*(10), 980–989. doi:10.1016/j.jaac.2010.05.017

Moore, S. A., Dowdy, E., Nylund-Gibson, K., & Furlong, M. J. (2017). *A latent class approach to complete mental health classification in adolescents.* Manuscript in preparation.

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

Morin, A. J. S., Maïano, C., Nagengast, B., Marsh, H. W., Morizot, J., & Janosz, M. (2011). General growth mixtures analysis of adolescents' developmental trajectories of anxiety: The impact of untested invariance assumptions and substantive interpretations. *Structural Equation Modeling: A Multidisciplinary Journal, 4*, 613–648. doi:10.1080/10705511.2011.607714

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

Muthén, L. K., & Muthén, B. O. (1998-2015). *Mplus user's guide* (7th Ed.). Los Angeles, CA: Muthén & Muthén.

Nylund, K. L. (2007). *Latent transition analysis: Modeling extensions and an application to peer victimization* (Doctoral Dissertation). Retrieved from http://www.statmodel.com/download/Nylund%20dissertation%20Updated1.pdf

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

Nylund, K., Bellmore, A., Nishina, A., & Graham, S. (2007). Subtypes, severity, and structural stability of peer victimization: What does latent class analysis say? *Child Development, 78*(6), 1706–1722. doi:10.1111/j.1467-8624.2007.01097.x

Nylund, K. L., Muthén, B., Nishina, A., Bellmore, A., & Graham, S. (2006). Stability and instability of peer victimization during middle school: Using latent transition analysis with covariates, distal outcomes, and modeling extensions [*unpublished manuscript*], University of California Los Angeles, Los Angeles, CA.

Nylund-Gibson, K., Grimm, R., Quirk, M., & Furlong, M. (2014). A latent transition mixture model using the three-step specification. *Structural Equation Modeling: A Multidisciplinary Journal, 21*(3), 439–454. doi:10.1080/10705511.2014.915375

Obradović, J., van Dulmen, M. H. M., Yates, T. M., Carlson, E. A., & Egeland, B. (2006). Developmental assessment of competence from early childhood to middle adolescence. *Journal of Adolescence 29*, 857–889. doi:10.1016/j.adolescence.2006.04.009

Overbeek, G., Vollebergh, W., Meeus, W., Engels, R., & Luijpers, E. (2001). Course, co-occurrence, and longitudinal associations of emotional disturbance and delinquency from adolescence to young adulthood: A six-year three-wave study. *Journal of Youth and Adolescence, 30*, 401–426. doi:10.1023/A:1010441131941

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

Ruchkin, V., Jones, S., Vermeiren, R., & Schwab-Stone, M. (2008). The Strengths and Difficulties Questionnaire: The self-report version in American urban and suburban youth. *Psychological Assessment, 20*, 175–182. doi:10.1037/1040-3590.20.2.175

Seligman, M. (2002). Positive psychology, positive prevention, and positive therapy. In C. R. Snyder & S. J. Lopez (Eds.), *Handbook of positive psychology* (pp. 3–9). New York, NY: Oxford University Press.

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

Severson, H. H., Walker, H. M., Hope-Doolittle, J., Kratochwill, T. R., & Gresham, F. M. (2007). Proactive, early screening to detect behaviorally at-risk students: Issues, approaches, emerging innovations, and professional practices. *Journal of School Psychology, 45*, 193–223. doi:2048/10.1016/j.jsp.2006.11.003

Scales, P. C. (1999). Reducing risks and building developmental assets: Essential actions for promoting adolescent health. *Journal of School Health, 69,* l13–119. doi:l0.111l/j.l746-1561.l 999.tb07219.x

Schwartz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics, 6*, 461–464. doi:10.1214/aos/1176344136

Stoep, A. V., McCauley, E., Thompson, K. A., Herting, J. R., Kuo, E. S., Stewart, D. G., … Kushen, S. (2005). Universal emotional health screening at the middle school transition. *Journal of Emotional and Behavioral Disorders, 13,* 213–223. doi:10.1177/10634266050130040301

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

Suldo, S., Thalji, A., & Ferron, J. (2011). Longitudinal academic outcomes predicted by early adolescents' subjective well-being, psychopathology, and mental health status yielded from a dual factor model. *The Journal of Positive Psychology: Dedicated to Furthering Research and Promoting Good Practice, 6*, 17–30. doi:10.1080/17439760.2010.536774

Suldo, S. M., Thalji-Raitano, A., Kiefer, S. M., & Ferron, J. M. (2016). Conceptualizing high school students' mental health through a dual-factor model. *School Psychology Review*, *45*(4), 434–457. doi:10.17105/SPR45-4.434-457

Verhulst, F. C., & van Wattum, P. J. (1993). Two-year stability of self-reported problems in an epidemiological sample of adolescents. *Acta Psychiatrica Scandanavica, 87,* 322–328. doi:10.1111/j.1600-0447.1993.tb03380.x

Vermunt, J. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis, 18,* 450–469. doi:10.1093/pan/mpq025

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

Westerhof, G. B., & Keyes, C. L. M. (2010). Mental illness and mental health: The two-continua model across the lifespan. *Journal of Adult Development, 17*, 110–119. doi:10.1007/s10804-009-9082-y

You, S., Furlong, M. J., Dowdy, E., Renshaw, T., Smith, D. C., & O'Malley, M. D. (2014). Further validation of the Social and Emotional Health Survey for high school students. *Applied Quality of Life Research, 9,* 997–1015. doi:10.1007/s11482-013-9282-2

Table 1

*Stability Patterns of Previous Longitudinal Dual-Factor Mental Health Research*

| Study | Group at Time 1 | Proportion Remaining in Group at Time 2 | Most Likely Transition Group at Time 2 (%) |
|---|---|---|---|
| Kelly et al. (2012) | Complete Mental Health | 85% | Symptomatic but Content (9%) |
| | Symptomatic but Content | 42% | Complete Mental Health (43%) |
| | Vulnerable | 29% | Complete Mental Health (46%) |
| | Troubled | 47% | Vulnerable (23%) |
| McMahan (2012) | Complete Mental Health | 80% | Symptomatic but Content (10%) |
| | Symptomatic but Content | 17% | Complete Mental Health (47%) |
| | Vulnerable | 27% | Complete Mental Health (45%) |
| | Troubled | 36% | Vulnerable (20%) or Symptomatic but Content (20%) |
| Compton (2016) | Complete Mental Health | 86% | Symptomatic but Content (10%) |
| | Symptomatic but Content | 44% | Complete Mental Health (38%) |
| | Vulnerable | 24% | Complete Mental Health (52%) |
| | Troubled | 61% | Symptomatic but Content (22%) |

Table 2

*Means and Standard Deviations of Mental Health Indicators for the Total Sample, Cohort A, and Cohort B*

| | BIS | BIO | EC | EL | INT | EXT |
|---|---|---|---|---|---|---|
| Grade 9 ($n$ = 457) | | | | | | |
| Total sample | 2.88(.50) | 3.11(.57) | 2.96(.49) | 3.28(.70) | 1.67(.47) | 1.76(.44) |
| Cohort A | 2.88(.50) | 3.11(.57) | 2.96(.49) | 3.28(.70) | 1.67(.47) | 1.76(.44) |
| Cohort B | — | — | — | — | — | — |
| Grade 10 ($n$ = 861) | | | | | | |
| Total sample | 2.96(.50) | 3.20(.57) | 3.10(.51) | 3.29(.69) | 1.63(.49) | 1.62(.47) |
| Cohort A | 3.04(.47) | 3.32(.51) | 3.19(.46) | 3.34(.66) | 1.52(.45) | 1.52(.46) |
| Cohort B | 2.87(.53) | 3.07(.61) | 3.00(.55) | 3.24(.73) | 1.75(.51) | 1.72(.46) |
| Grade 11 ($n$ = 758) | | | | | | |
| Total sample | 3.03(.51) | 3.28(.55) | 3.22(.48) | 3.32(.69) | 1.56(.48) | 1.53(.47) |
| Cohort A | 3.03(.54) | 3.27(.58) | 3.22(.50) | 3.34(.71) | 1.55(.48) | 1.48(.48) |
| Cohort B | 3.02(.48) | 3.28(.52) | 3.23(.46) | 3.30(.67) | 1.57(.48) | 1.57(.47) |
| Grade 12 ($n$ = 306) | | | | | | |
| Total sample | 3.10(.53) | 3.31(.56) | 3.26(.51) | 3.39(.72) | 1.60(.51) | 1.48(.47) |
| Cohort A | — | — | — | — | — | — |
| Cohort B | 3.10(.53) | 3.31(.56) | 3.26(.51) | 3.39(.72) | 1.60(.51) | 1.48(.47) |

*Note.* BIS = belief in self, BIO = belief in others, EC = emotional competence, EL = engaged living, INT = internalizing distress, EXT = externalizing distress. The mean-value range for BIS, BIO, and EC was 1 to 4; for EL was 1 to 4.67; and for INT and EXT was 1 to 3.

Table 3

*Information Used to Evaluate Tested LPA Dual-Factor Mental Health Models*

| Model | Number of classes | Log likelihood | BIC | *p*-value of BLRT | *p*-value of LMRT | Entropy | BF | cmP | Class Prevalence |
|---|---|---|---|---|---|---|---|---|---|
| Grade 9 - Model 1 (*n* = 457) | 1 | -2154.43 | 4382.61 | — | — | 1.00 | <.001 | <.001 | 1.00 |
| | 2 | -1919.37 | 3955.53 | <.001 | **<.001** | 0.72 | <.001 | <.001 | .50, .50 |
| | 3 | -1831.09 | 3821.98 | <.001 | 0.582 | 0.79 | <.001 | <.001 | .10, .32, .58 |
| | 4 | -1775.86 | **3754.55** | <.001 | **0.018** | 0.77 | <.001 | <.001 | .10, .20, .24, .47 |
| | 5 | -1743.02 | 3731.90 | <.001 | 0.401 | 0.80 | 0.002 | 0.002 | .01, .12, .18, .22, .47 |
| | 6 | -1715.46 | 3719.80 | <.001 | 0.242 | 0.77 | <.001 | **0.998** | .01, .07, .14, .19, .20, .40 |
| Grade 9 - Model 2 (*n* = 457) | 1 | -2154.43 | 4382.61 | — | — | 1.00 | <.001 | <.001 | 1.00 |
| | 2 | -1879.02 | 3911.70 | <.001 | <.001 | 0.77 | <.001 | <.001 | .41, .59 |
| | 3* | -1769.82 | 3773.21 | <.001 | 0.021 | 0.77 | <.001 | <.001 | .19, .30, .51 |
| | 4* | -1718.55 | **3750.57** | NC | **0.039** | 0.80 | 2.180 | **0.69** | .14, .19, .21, .46 |
| | 5* | -1679.38 | **3752.13** | NC | 0.235 | 0.81 | **>10** | 0.31 | .05, .12, .19, .22, .42 |
| | 6* | -1649.52 | 3772.31 | NC | 0.124 | 0.82 | <.001 | <.001 | .03, .05, .13, .16, .23, .39 |
| Grade 10 - Model 1 (*n* = 861) | 1 | -4099.00 | 8279.09 | — | — | 1.00 | <.001 | <.001 | 1.00 |
| | 2 | -3555.22 | 7238.85 | <.001 | <.001 | 0.81 | <.001 | <.001 | .31, .69 |
| | 3 | -3356.31 | **6888.33** | <.001 | **<.001** | 0.79 | <.001 | <.001 | .14, .32, .53 |
| | 4 | -3296.22 | **6815.45** | <.001 | 0.438 | 0.78 | <.001 | <.001 | .07, .19, .25, .49 |
| | 5 | -3248.91 | 6768.15 | <.001 | 0.163 | 0.79 | <.001 | <.001 | .06, .07, .12, .28, .46 |
| | 6 | -3210.04 | 6737.71 | <.001 | 0.221 | 0.78 | <.001 | **1.00** | .04, .05, .12, .16, .24, .38 |
| Grade 10 - Model 2 (*N* = 861) | 1 | -4099.00 | 8279.09 | — | — | 1.00 | <.001 | <.001 | 1.00 |
| | 2* | -3498.59 | 7166.14 | <.001 | 0.002 | 0.75 | <.001 | <.001 | .45, .55 |
| | 3* | -3238.72 | **6734.25** | NC | 0.006 | 0.81 | <.001 | <.001 | .22, .23, .55 |
| | 4* | -3142.76 | **6630.17** | NC | **0.169** | 0.78 | <.001 | <.001 | .13, .17, .25, .44 |
| | 5* | -3076.64 | 6585.80 | NC | 0.102 | 0.75 | <.001 | <.001 | .10, .11, .21, .27, .31 |
| | 6* | -3024.31 | 6568.99 | NC | 0.142 | 0.77 | <.001 | **1.00** | .03, .09, .13, .19, .27, .29 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Grade 11 - Model 1 (*n* = 758) | 1 | -3510.00 | 7099.56 | — | — | 1.00 | <.001 | <.001 | 1.00 |
| | 2 | -3023.55 | 6173.09 | <.001 | <.001 | 0.79 | <.001 | <.001 | .37, .63 |
| | 3 | -2860.97 | **5894.33** | <.001 | 0.040 | 0.80 | <.001 | <.001 | .13, .33, .54 |
| | 4 | -2791.14 | **5801.09** | <.001 | 0.010 | 0.77 | <.001 | <.001 | .06, .21, .29, .44 |
| | 5 | -2720.24 | **5705.70** | <.001 | **0.003** | 0.80 | 0.005 | 0.01 | .05, .12, .17, 24, .42 |
| | 6 | -2691.74 | **5695.13** | <.001 | 0.192 | 0.82 | <.001 | **0.99** | .01, .06, .12, .17, .24, .41 |
| Grade 11 - Model 2 (*n* = 758) | 1 | -3510.00 | 7099.56 | — | — | 1 | <.001 | <.001 | 1.00 |
| | 2* | -2950.43 | 6066.62 | NC | <.001 | 0.77 | <.001 | <.001 | .48, .52 |
| | 3* | -2712.38 | 5676.72 | <.001 | 0.137 | 0.84 | <.001 | <.001 | .11, .32, .57 |
| | 4* | -2611.28 | 5560.73 | NC | 0.310 | 0.79 | <.001 | 1.00 | .14, .20, .21, .45 |
| | 5 | No Convergence | | | | | | | |
| | 6 | No Convergence | | | | | | | |
| Grade 12 - Model 1 (*n* = 306) | 1 | -1482.459 | 3033.601 | — | — | 1.00 | <.001 | <.001 | 1.00 |
| | 2 | -1299.777 | 2708.302 | <.001 | 0.017 | 0.76 | <.001 | <.001 | .44, .56 |
| | 3 | -1210.031 | 2568.875 | <.001 | 0.001 | 0.84 | <.001 | <.001 | .08, .38, .53 |
| | 4 | -1165.242 | **2519.363** | <.001 | **0.001** | 0.84 | 0.218 | 0.17 | .08, .21, .34, .37 |
| | 5 | -1143.689 | **2516.321** | <.001 | 0.421 | 0.82 | *9.840* | **0.76** | .08, .13, .19, .26, .34 |
| | 6 | -1125.943 | **2520.894** | <.001 | 0.115 | 0.84 | <.001 | 0.08 | .06, .07, .13, .14, .27, .33 |
| Grade 12 - Model 2 (*n* = 306) | 1 | -1482.459 | 3033.601 | — | — | 1.00 | <.001 | <.001 | 1.00 |
| | 2* | -1262.427 | 2667.944 | NC | <.001 | 0.95 | <.001 | <.001 | .19, .81 |
| | 3* | -1171.73 | 2560.956 | NC | 0.063 | 0.84 | <.001 | **1.00** | .18, .24, .59 |
| | 4 | No Convergence | | | | | | | |
| | 5 | No Convergence | | | | | | | |
| | 6 | No Convergence | | | | | | | |

*Note*. Bolded values indicate preferred model for a given fit index. Shaded rows indicate model selected for each year.
*log likelihood starting and best-solution values did not converge, indicating model instability

Table 4

*Percent of Students in Each of the Dual-Factor Mental Health Classes in Grades 9 through 12*

| Class | Grade 9 | Grade 10 | Grade 11 | Grade 12 |
|---|---|---|---|---|
| Complete Mental Health | 19.14 | 25.74 | 20.52 | 35.75 |
| Moderately Mentally Healthy | 49.98 | 48.52 | 43.79 | 33.44 |
| Symptomatic but Content | 28.06 | 18.70 | 29.03 | 23.90 |
| Troubled | 2.80 | 7.04 | 6.67 | 6.91 |

Table 5

*Conditioned Latent Transition Probability Estimates of First-Order Effects*

| Class | Complete Mental Health | Moderately Mentally Healthy | Symptomatic but Content | Troubled |
|---|---|---|---|---|
| Grade 9 | | Grade 10 | | |
| Complete Mental Health | **0.79** | 0.19 | 0.02 | 0.00 |
| Moderately Mentally Healthy | 0.20 | **0.70** | 0.10 | 0.00 |
| Symptomatic but Content | 0.02 | 0.33 | **0.46** | 0.19 |
| Troubled | 0.00 | 0.22 | 0.19 | **0.60** |
| Grade 10 | | Grade 11 | | |
| Complete Mental Health | **0.61** | 0.39 | 0.00 | 0.00 |
| Moderately Mentally Healthy | 0.08 | **0.63** | 0.26 | 0.04 |
| Symptomatic but Content | 0.04 | 0.15 | **0.69** | 0.12 |
| Troubled | 0.04 | 0.06 | 0.51 | **0.40** |
| Grade 11 | | Grade 12 | | |
| Complete Mental Health | **0.93** | 0.00 | 0.07 | 0.01 |
| Moderately Mentally Healthy | 0.38 | **0.34** | 0.24 | 0.12 |
| Symptomatic but Content | 0.00 | 0.62 | **0.26** | 0.12 |
| Troubled | 0.03 | 0.08 | 0.64 | **0.25** |

*Note*. Bolded values indicate the proportion of students who remained in the same mental health class across comparison points.

Table 6

*Conditioned Latent Transition Probability Estimates of Second-Order Effects*

| Class | Complete Mental Health | Moderately Mentally Healthy | Symptomatic but Content | Troubled |
|---|---|---|---|---|
| Grade 9 | Grade 11 | | | |
| Complete Mental Health | **0.65** | 0.33 | 0.02 | 0.00 |
| Moderately Mentally Healthy | 0.13 | **0.58** | 0.27 | 0.02 |
| Symptomatic but Content | 0.05 | 0.36 | **0.59** | 0.20 |
| Troubled | 0.17 | 0.06 | 0.50 | **0.27** |
| Grade 10 | Grade 12 | | | |
| Complete Mental Health | **0.73** | 0.03 | 0.23 | 0.01 |
| Moderately Mentally Healthy | 0.32 | **0.46** | 0.17 | 0.04 |
| Symptomatic but Content | 0.06 | 0.41 | **0.53** | 0.07 |
| Troubled | 0.04 | 0.44 | 0.06 | **0.46** |

*Note*. Bolded values indicate the proportion of students who remained in the same mental health class across comparison points.

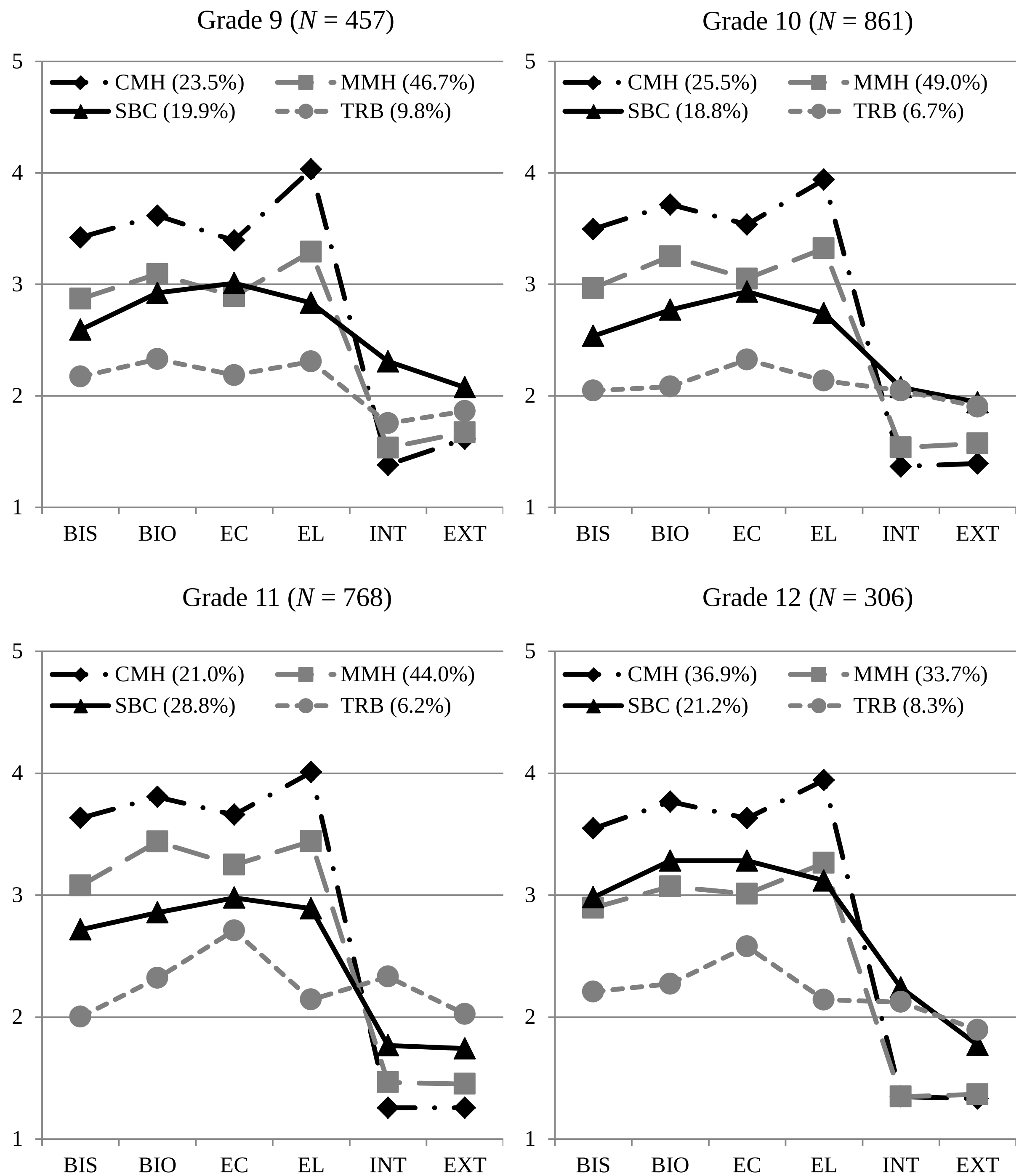
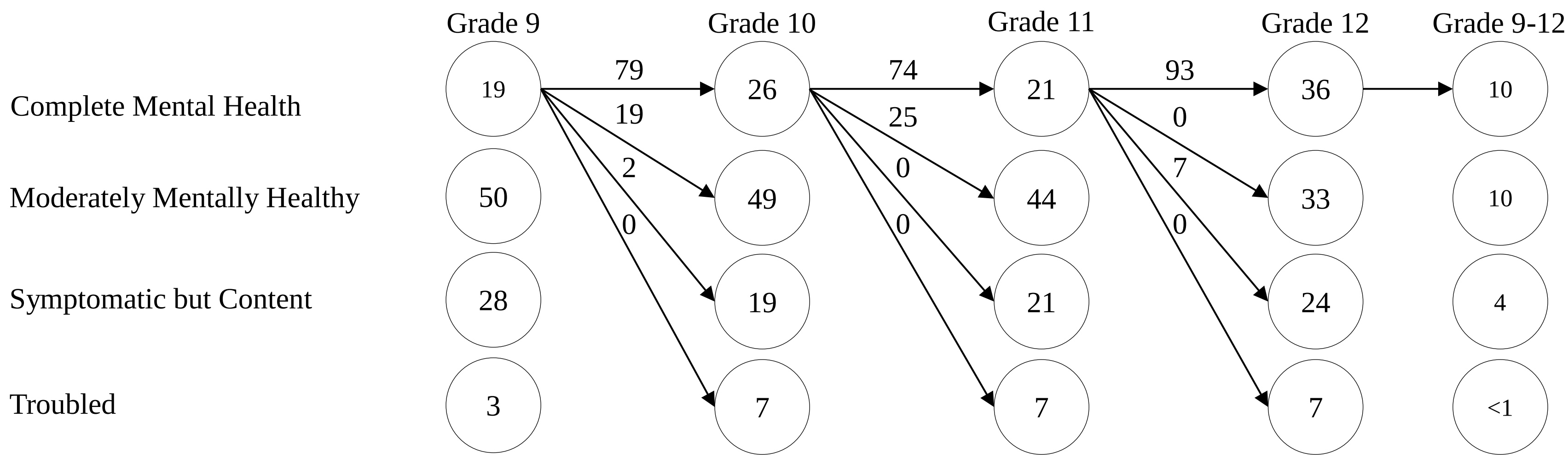
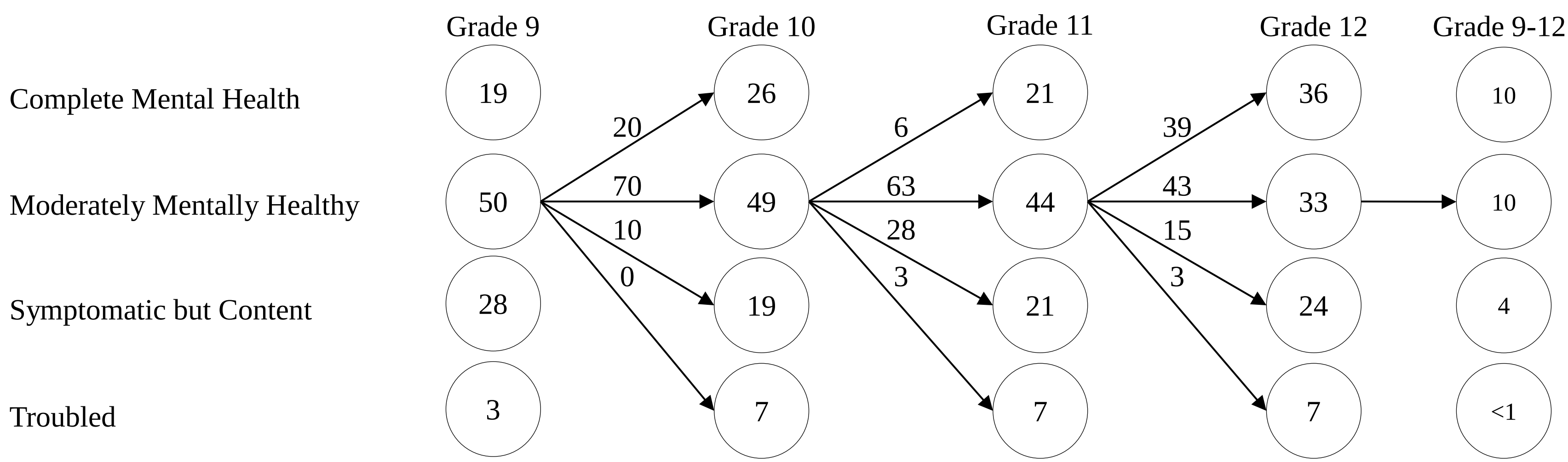



*Figure 1*. Dual-factor mental health profile plots displaying estimated means for the four-class solution for each of Grade 9 through Grade 12. Class size information is presented in the legend. *Note*. BIS = belief in self, BIO = belief in others, EC = emotional competence, EL = engaged living, INT = internalizing distress, EXT = externalizing distress. CMH = complete mental health class, MMH = moderately mentally healthy class, SBC = symptomatic but content class, TRB = troubled class. The mean-value range for BIS, BIO, and EC was 1 to 4; for EL was 1 to 4.67; and for INT and EXT was 1 to 3.


Grade 9
Grade 10
Grade 11
Grade 12
Grade 9-12
Complete Mental Health
Moderately Mentally Healthy
Symptomatic but Content
Troubled
19
50
28
3
79
19
2
0
26
49
19
7
74
25
0
0
21
44
21
7
93
0
7
0
36
33
24
7
10
10
4
<1


Grade 9
Grade 10
Grade 11
Grade 12
Grade 9-12
Complete Mental Health
Moderately Mentally Healthy
Symptomatic but Content
Troubled
19
50
28
3
20
70
10
0
26
49
19
7
6
63
28
3
21
44
21
7
39
43
15
3
36
33
24
7
10
10
4
<1

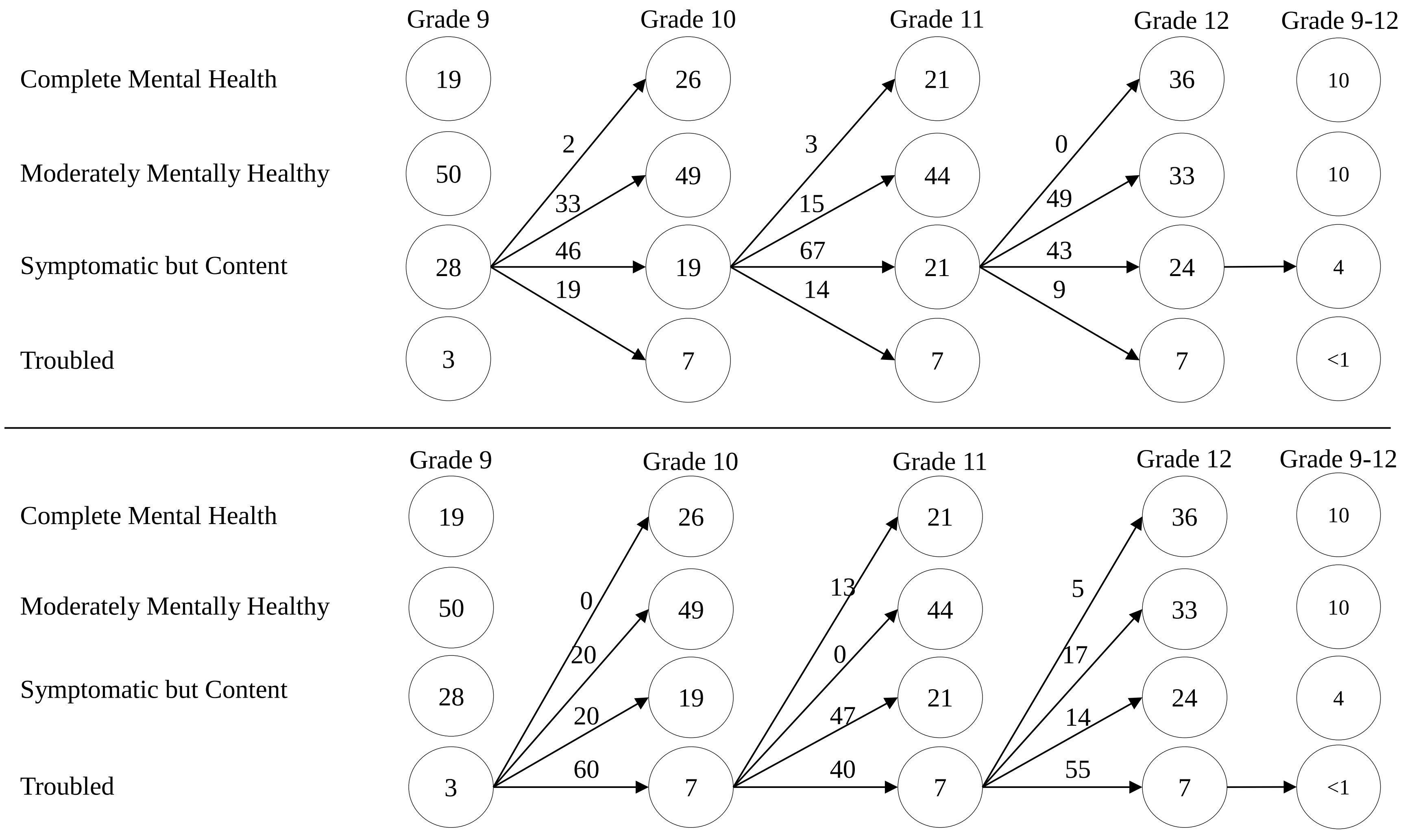



*Figure 2.* Four-year stability patterns for each of the *complete mental health*, *moderately mentally healthy*, *symptomatic but content*, and *troubled* profiles, respectively, based on the final estimated LTA model from Grade 9 to Grade 12. Numbers in circles refer to percent of students in each mental health profile. Numbers above arrows indicate the percentage of students who transition from one mental health profile to another.

## Summary and Concluding Discussion

Empirical classification and stability of dual-factor mental health profiles were examined in two studies. Study 1 investigated LPA identified groups for 332 adolescents for each of Grades 9, 10, and 11. The relation of latent class membership to individual demographic indicators and Grade 12 academic and social-emotional outcomes offered preliminary validation of the emerging mental health profiles. Extending Study 1, Study 2 examined the longitudinal stability of empirically identified dual-factor mental health profiles. Using two cohorts of students totaling 875 participants, mental health groups were first identified in cross-sectional measurement models. Then, a longitudinal LTA model was specified to examine patterns in stability across Grades 9 to 12.

### An Empirical Approach to Classification

In both Study 1 and Study 2, a four-class model was selected as the optimal model for each grade year. The four identified mental health profiles were labeled: *complete mental health* (high well-being and low distress), *moderately mentally healthy* (high-average well-being and low distress), *symptomatic but content* (average to high-average well-being and average to above-average distress), and *troubled* (average to low-average well-being and above-average distress). Consistent with previous research, the greatest percentage of students fit a more desirable mental health profile characteristic of moderate to high levels of well-being and low distress (e.g., *complete mental health*, *moderately mentally healthy*) than a less desirable mental health profile characteristic of lower levels of well-being and higher levels of distress (e.g., *symptomatic but content*, *troubled*). Across grade years in both studies, the smallest percentage of students fit a *troubled* profile whereas the largest percentage of students tended to fit a *moderately mentally healthy* profile.

Consistent with previous research, *complete mental health*, *symptomatic but content*, and *troubled* profiles were identified in the current studies. However, a vulnerable profile, characteristic of low levels of both well-being and distress was not identified. The inability to detect a vulnerable group in each study may be due to a number of factors. For example, given that both studies utilized participants from one high school, results may reflect sample specific characteristics. However, when dichotomous, sample-specific cut-point criteria are used, as in previous dual-factor research, individuals were most often assigned to either a low or high group based on how their score compared to other students in the sample. This criterion-driven definition of groups may have resulted in artificial separation between individuals fitting similar well-being profiles. For example, among those classified as having low distress, people falling in the upper range of the "low" criteria would have been classified as having low well-being (e.g., vulnerable) whereas those on the lower range of the "high" criteria would have been classified as having high well-being (e.g., complete mental health). Thus, the presence of a vulnerable group in previous research may represent an artifact of cut point classification; when groups were formed based upon similarities in responses in the current studies, a vulnerable profile was not evident. Finally, it is also possible that the students fitting a vulnerable profile, which has typically included the fewest number of students in previous research (e.g., 5% [Venning et al., 2013] to 13% [Suldo & Shaffer, 2008]), were too few to be detected in the current studies. Additional research is warranted to replicate the empirical approach to classification and whether similar profiles emerge in new samples of students. Moreover, research comparing cut point and empirical approaches to classification, for example investigating differences in classification approaches is needed. For example, future research may be able to answer: If students in the current study had been grouped using cut point criteria, thus forcing the presence of a languishing group, what profile would these students fit in an LPA framework?

The variability observed particularly in levels of well-being between classes in each cross-sectional examination in the current studies highlights a key limitation in cut score approaches to classification. Use of an LPA approach demonstrated that the mental health profiles exhibited average score differences across strength indicators measuring well-being, in particular. When rationally-determined cut-score approaches are used these differences are simplified into only two levels of well-being (i.e., low versus high). However, results of Study 1 demonstrated significant differences between the *complete mental health* and *moderately mentally healthy* groups on positive outcomes. Although each profile was characteristic of low distress, they varied with respect to well-being. Youth fitting a *complete mental health* profile were flourishing, with the highest levels of well-being across grade years and higher reported levels of prosocial contribution to community and life satisfaction. These results suggest that having above average strengths and low distress may be insufficient for thriving. Rather, youth with the highest levels of well-being may meaningfully differ from others with moderately high levels of well-being. Moreover, Study 2 similarly demonstrated that, although both *complete mental health* and *moderately mentally healthy* groups demonstrated strong stability, youth fitting a *complete mental health* profile exhibited the greatest levels of stability across comparisons. These differences are not able to be recognized when a cut-score approach is used. Therefore, the current cut-score approach to classification may be oversimplifying variation among mental health groups that is related to differences on adolescent outcomes.

## Stability of Dual-Factor Mental Health

In Study 1, structural stability of the four identified dual-factor mental health groups was observed across Grades 9 to 11. The LPA class enumeration process pointed to a four-class solution for each grade year. In Study 2, prior to specifying the longitudinal LTA to examine stability of individuals' dual-factor mental health, cross-sectional LPA models were tested. Although a four-class solution was selected for each grade year in Study 2 (i.e., Grades 9 to 12), the class enumeration process was more nuanced. As noted in the discussion for Study 2, model fit was less clear in this larger, combined sample with the four-class solution representing one plausible solution, particularly for Grades 10 and 11. However, examining each of the four-class solutions for Study 1 and Study 2, the four emerging latent profiles were similar in conceptual interpretation over time. Thus, Study 1 and Study 2 provided preliminary evidence for the structural stability of empirically defined dual-factor mental health profiles over the high school years. Additional research is needed to determine if a four-class solution with similar latent profiles emerges in independent samples.

The proportion of students fitting the *complete mental health*, *moderately mentally healthy*, *symptomatic but content*, and *troubled* profiles was observed to fluctuate in the cross-sectional solutions for each grade year in both Study 1 and 2, providing evidence that adolescents were transitioning between mental health classes over time. LTA was conducted in Study 2 to investigate the degree to which individuals exhibited stability or instability in their dual-factor mental health status. The LTA model building process supported a final solution consisting of full measurement invariance, non-stationary transitions (i.e., probability of transitioning between classes allowed to vary over each year), and a second-order effect indicating a lasting impact of mental health status. Results of the LTA model enabled examination of stability over four-years in addition to one- and two-year intervals. Across four-years, approximately one-quarter of participants remained in the same class each year. Adolescents in the *complete mental health* and *moderately mentally healthy* groups exhibited the greatest four-year stability, followed by those initially fitting a *symptomatic but content* profile. Less than 1% of youth classified in the *troubled* group in Grade 9 remained in the *troubled* group in each of the following years. Stability estimates across one- and two-year comparisons demonstrated similar patterns, with students exhibiting *complete mental health* the most likely to remain in the *complete mental health* group one and two years later, on average, and students in the *troubled* group the least likely to remain in the *troubled* group one and two years later.

Consistent with previous research examining the stability of dual-factor mental health, youth in more desirable mental health groups (i.e., *complete mental health* and *moderately mentally healthy*) tended to be more likely to stay in these groups than to transition to less desirable mental health groups (i.e., *symptomatic but content* or *troubled*). However, contrary to previous research which found the youth within a *troubled* group to exhibit the second greatest stability, in the current study, youth fitting a *troubled* profile exhibited the least stability, on average, when compared to the stability of students in the other three mental health profiles. This difference may reflect differences in measurement tools (e.g., a screening instrument was used to assess distress in the current study, whereas previous research has tended to use more comprehensive clinical measures) or classification method (e.g., the *symptomatic but content* profile, previously found to have the least stability, may be more stable when formed via empirical methods). Although the rank ordering of average stability estimates differs from previous research, the proportion of youth who remained in the troubled group across one-year periods in the current study (25% from Grade 11 to 12, 40% from Grade 10 to 11, and 60% from Grade 9 to 10, 42% on average across one-year comparisons), is consistent with previous research examining stability over one-year or less with middle school students (47%; Kelly et al., 2012), high school students (36%; McMahan, 2012), and early elementary students (61%; Compton, 2016).

Among students whose mental health status changed from one grade to the next, most were likely to transition into a more desirable mental health class than into a less desirable mental health class. For example, among students in profiles demonstrating average to above-average distress in one grade, those who changed classes were more likely to show improvement in their levels of well-being or distress. However, it was very unlikely for youth in a *troubled* class to transition to a *complete mental health* class. Current results were congruent with previous research that indicated a trend toward *complete* or *moderate* mental health over time. Despite the general trends observed in the stability and instability of adolescents' dual-factor mental health, variability was observed in stability and instability estimates within the one- and two-year comparisons transition comparison. A LTA model assuming equivalence in transition probabilities over one-year comparisons was found to have significantly worse fit over a model allowing transition probabilities to be freely estimated. This variability indicates that patterns in stability of dual-factor mental health may vary across grade levels and offers support for regular monitoring of youth's dual-factor mental health status so as to most accurately inform promotion, prevention, and intervention efforts.

## Conclusion

Results from the current studies provide additional support for a dual-factor model of mental health and extend its application to empirical classification methods, such as LPA. The present findings may further be used to inform school-based dual-factor mental health efforts, particularly with adolescents. Results highlight the need to critically examine methods used to classify mental health as well as to examine whether the ability to predict future outcomes differs based on classification method used. Based on the present findings, the current cut-score approaches for defining dual-factor mental health groups may be insufficient for describing meaningful variation in students' mental health profiles. However, few school-based practitioners may have the requisite training and statistical skills to examine their students' dual-factor mental health using an empirical LPA approach. Thus, additional work is needed to develop methods for translating LPA classification parameters into a framework that can be used by school-based professionals.

Nevertheless, regularly monitoring youths' mental is recommended. In particular, results suggest that assessing youths' dual-factor mental health status on at least a yearly basis (e.g., via universal screening) is needed to accurately inform intervention decisions. That is, assessment results can be used to identify students who may benefit from each of universal, selected, and targeted supports. When designing interventions, current results offer support for interventions designed to promote well-being in addition to those designed to ameliorate distress such that optimal development and thriving are supported for all students. Monitoring and intervening within a dual-factor mental health framework, with emphasis placed on promoting complete mental health, enables all students to benefit from school-based mental health efforts.

## Additional References


Boyce, W. T., Essex, M. J., Woodward, H. R., Measelle, J. R., Ablow, J. C., & Kupfer, D. J. (2002). The confluence of mental, physical, social and academic difficulties in middle childhood. I: Exploring the "headwaters" of early life morbidities. *Journal of the American Academy of Child and Adolescent Psychiatry, 41*, 580–587. doi:10.1097/00004583-200205000-00016

Bradley, R., Doolittle, J., & Bartolotta, R. (2008). Building on the data and adding to the discussion: The experiences and outcomes of students with emotional disturbance. *Journal of Behavioral Education, 17,* 4–23. doi:10.1007/s10864-007-9058-6

Cash, R. E., & Nealis, L. K. (2004). *Mental health in the schools: It's a matter of public policy.* Paper presented at the National Association of School Psychologists Public Policy Institute, Washington, DC.

Farmer, E. Z., Burns, B. J., Phillips, S. D., Angold, A., & Costello, E. (2003). Pathways into and through mental health services for children and adolescents. *Psychiatric Services, 54,* 60–66. doi:10.1176/appi.ps.54.1.60

Kataoka, S. H., Zhang, L., & Wells, K. B. (2002). Unmet need for mental health care among US children: Variation by ethnicity and insurance status. *American Journal of Psychiatry, 159,* 1548–1555. doi:10.1176/appi.ajp.159.9.1548

Kleiver, A., & Cash, R. E. (2005). Characteristics of a public health model of a mental health service delivery. *Communique, 34*(3), 19.

National Association of School Psychologists. (2010a). *Model for comprehensive and integrated school psychological services.* Bethesda, MD: National Association of School Psychologists.

National Association of School Psychologists. (2010b). *Standards for graduate preparation of school psychologists.* Bethesda, MD: National Association of School Psychologists.

Roderick, M., Arney, M., Axelman, M., DaCosta, K., Steiger, C., Stone, S., … Waxman, E. (1997, July). *Habits hard to break: A new look at truancy in Chicago's public high schools.* Research brief. Chicago, IL: University of Chicago School of Social Service Administration. Retrieved from https://ccsr.uchicago.edu/publications/habits-hard-break-new-look-truancy-chicagospublic-high-schools

Rones, M., & Hoagwood, K. (2000). School-based mental health services: A research review. *Clinical Child and Family Psychology Review, 3,* 223–241. doi:10.1023/A:1026425104386

Strobach, K. V. (2015). *The every student succeeds act and school psychologists.* Retrieved from https://www.nasponline.org/research-and-policy/policy-matters/the-every-student-succeeds-act-and-school-psychologists