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Student perceptions of classroom goal structure: Methodological considerations and person-context interactions

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Student Perceptions of Classroom Goal Structure: Methodological Considerations and Person-Context Interactions

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSPHY

in Education

by

Arena C. Lam

Dissertation Committee:
Distinguished Professor Jacquelynne S. Eccles, Chair
Assistant Professor AnneMarie M. Conley, Co-Chair
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2015

DEDICATION

To

My high school sweetheart, Hanh Lam

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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The School of Education has been my second home for five years and this time spent was made memorable by the friendships made and support received from classmates and colleagues. I've enjoyed the enriching conversations from the many lab meetings throughout the years: CAMP, SEDL, ARL, and CRCL. You have all pushed my thinking and stretched me further than I could have possibly done alone. I'd like to thank C4 and the Kakao group (and A-team) for providing laughter, emotional and statistical support, and being a source of sanity during crazy times.

I'd also like to thank my family, friends, and dogs (how could I forget them?) for providing unrelenting support despite not fully understanding what I do. Lastly, all of this would not have been possible without my husband, Hanh. He was the one who persuaded me to apply to Ph.D. programs, held me up during the times when I didn't believe in myself, been my biggest cheerleader, and even helped format tables. For you I am most grateful.

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PUBLISHED MANUSCRIPTS

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Schenke, K., **Lam A. C.,** Conley, A. M., & Karabenick, S. A. (2015). Adolescents' help seeking in mathematics classrooms: Relations between achievement and perceived classroom environmental influences over one school year. *Contemporary Educational Psychology, 41*, 133-146. http://dx.doi.org/10.1016/j.cedpsych.2015.01.003

Chang, A., & Mahoney, J.L. (2013). A longitudinal comparison of parent and child influence on sports participation. *Journal of Youth Development—Bridging Research and Practice, 8*(3), 67-81.

MANUSCRIPTS UNDER REVIEW

Schenke, K., **Lam, A. C.,** Rutherford, T., & Bailey, D. H. (under review). Construct confounding among predictors of mathematics achievement.

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Rutherford, T., Schenke, K., **Lam, A. C.,** Lee, D. S., Leyrer, J., Young, N. S., Tran, C., & Graham, J. D. (in preparation). Integrating cognitive and motivation trainings for a "Brain Boost": Development and randomized experiment of a pilot program.

Lam, A. C., Rutherford, T., & Schenke, K. (in preparation). I can do it! Expectancy as a mediator of the ST Math effect on math achievement.

Lam, A. C., O'Dowd, D., Edinger, A., Williams, A., & Conley, A. M. (in preparation). Click to Compete! Using group clicker competitions to increase peer networks and achievement in large introductory Biology courses.

Schenke, K., **Lam, A. C.,** Ruzek, E.A., Conley, A.M., & Karabenick, S. A. (in preparation). Latent profile analysis of middle school students' perceptions of math classrooms' goal structures.

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Safavian, N., **Lam, A. C.,** Lauermann, F., Banerjee, M., & Eccles, J. S. (2015, May). An examination of the associations between gender and STEM-related career aspirations. Poster accepted to the National Science Foundation ADVANCE/Research on Gender in Science and Engineering workshop, Baltimore, MD.

Schenke, K., **Lam, A. C.,** Ruzek, E. A., Conley, A. M., Karabenick, S. A., & Eccles, J. S. (2015, April). Heterogeneity of student perceptions of the classroom climate: A latent profile approach. In Eccles, J. S. (Chair), "Student Heterogeneity in the Classroom: Precursors and Links to Outcomes." Paper session conducted at the annual meeting of the American Educational Research Association, Chicago, IL.

Schenke, K., Rutherford, T. **Lam, A. C.,** & Lee, D. S. (2015, March). Working memory and self-concept as determinants of achievement in elementary mathematics: Reciprocal relations across three years. Poster accepted to the annual meeting of Society for Research in Child Development, Philadelphia, PA.

Chang, A., Ruzek, E., Schenke, K., Conley, A. M., & Karabenick, S. A. (2014, April). Using multilevel confirmatory factor analysis to understand students' perceptions of classroom goal structure. In Middleton, M. J. (Chair), "Achievement Goal Theory: New Research and Applications." Paper session conducted the annual meeting of the American Educational Research Association, Philadelphia, PA.

Chang, A., Rutherford, T., & Schenke, K. (2014, April). I can do it!: Expectancy as a mediator of the STMath effect of math achievement. In Clements, D. H. (Chair), "Facets of Large-Scale Evaluation: An Illustration of Outcomes, Mediators, and Moderators." Paper symposium conducted at the annual meeting of the American Educational Research Association, Philadelphia, PA.

Chang, A. (2013, November). Click to compete! Group competition to support engagement and interaction in undergraduate Biology lectures. Poster presented at the biennial conference of the Southwest Consortium for Innovative Psychology in Education, Tucson, AZ.

Chang, A., Schenke, K., Conley, A. M., & Karabenick, S. A. (2013, April). Mathematics achievement, help seeking, and classroom goal structures. Poster presented at the annual meeting of the American Educational Research Association, San Francisco, CA.

Schenke, K., **Chang, A.,** Ruzek, E., Karabenick, S., & Conley, A. M. (2013, April). Classroom influences on students' help-seeking behavior. In Newman, R. S. (Chair), "The Role of Motivation in Help-Seeking: Peers, Processes, and Classroom Perceptions." Symposium conducted at the annual meeting of the American Educational Research Association, San Francisco, CA. (featured in Education Week's blog **http://blogs.edweek.org/edweek/inside-school-research/2013/04/aera_socially_savvy_students_g.html**)

Rutherford, T., Lee, D. S., Schenke, K., **Chang, A.,** Tran, C., Young, N. S. Conley, A. M., Graham, J. D., Leyrer, J., & Martinez, M. E. (2013, April). Brain boost: Randomized trial of a program to enhance intelligence in elementary and middle school. Poster presented at the annual meeting of the American Educational Research Association, San Francisco, CA.

Schenke, K., **Chang, A.,** Rutherford, T., Lee, D. S., Tran, C., Young, N. S., Leyrer, J., Graham, J., & Martinez, M.E. (2012, August). Brain Boost: A model for enhancing cognitive ability in an after school environment. Poster presented at the annual meeting of the American Psychological Association, Orlando, FL.

Chang, A., & Mahoney, J. L. (2012, April). A longitudinal comparison of parent and child influence on sports participation. Roundtable session conducted at the annual meeting of the American Education Research Association, Vancouver, British Columbia, Canada.

Chang, A., & Mahoney, J.L. (2011, December). The adult-child relationship's influence on task-related motivation and participation. Poster accepted for the annual meeting of the California Educational Research Association, Anaheim, CA.

Rutherford, T., Hinga, B., **Chang, A.**, Conley, A.M., & Martinez, M.E. (2011, August). The effect of ST Math software on standardized test scores via improvement in mathematics expectancy. Paper presented at the annual meeting of the American Psychological Association, Washington, D.C.

Safavian, N., **Chang, A.**, Conley, A.M., & Karabenick, S. (2011, August). Expectancies and values in mathematics teaching. Poster presented at the annual meeting of the American Psychological Association, Washington, D.C.

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January 2015 Invited presentation, "How Can We Use Student Experiences of the Classroom to Characterize Classrooms?"
Motivation Meeting
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March 2014 Guest lecture, "The Role of Out-of-School Time (OST) in Adolescent Social Development"
EDUC 185: Social Development in Education
UC Irvine

April 2011 Guest lecture, "Motivation and Out-of-School Time"
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UC Irvine

October 2010 Guest lecture, “Motivation and Out-of-School Time”
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RESEARCH EXPERIENCE

2015 Graduate Student Researcher
Achievement Research Lab
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NSF-funded project using three longitudinal datasets to investigate the impact of classroom and family environments on the development of student achievement beliefs and STEM career aspirations and attainment over 30-year span.

2013-2014 Project Researcher
Enhancing Peer Networks and Student Motivation in STEM Lectures
Faculty Lead Dianne O’Dowd (UC Irvine)
Intervention using clicker activities designed to support undergraduate students’ formation of peer learning peer networks and engagement in large introductory Biology lectures.

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California Motivation Project (CAMP)
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2011-2014 Graduate Student Researcher
Spatial Temporal Mathematics at Scale (ST Math)
P.I. George Farkas (UC Irvine)
IES-funded Goal Three collaborative project with Orange County Department of Education and MIND Research Institute to evaluate ST Math software program in a randomized field experiment in 52 low-performing schools in Southern California.

2011-2012 Graduate Student Researcher
University-Community Partnership for an After-School Education
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UC Links-funded collaborative project involving 7 afterschool programs to provide classroom instruction, training opportunities, and supervised fieldwork for program providers enrolled in School of Education courses.

2010-2012 Project Researcher
Brain Boost
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Integrated cognitive and motivation intervention aimed at upper and elementary middle school students.

TEACHING EXPERIENCE

Fall 2014 Teaching Assistant, UC Irvine School of Education
EDUC 173: Cognition and Learning in Educational Settings

Summer 2014 Teaching Assistant, UC Irvine School of Education
EDUC 40: Theories of Development and Learning Applied to Education

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EDUC 203 Advanced Concepts in Learning and Cognition

2012-2014 Research Supervisor/Discussion Leader, UC Irvine School of Education
EDUC 198: Directed Research in Education

Spring 2010 Teaching Assistant, UC Irvine School of Education
EDUC 108: Adolescent Development in Education

Fall 2010 Teaching Assistant, UC Irvine School of Education
EDUC 50: Issues in K-12 Education

2009-2010 No Child Left Behind Tutor, Academic Advantage
Mountain View School District, El Monte, CA
Duties: Tutored students in Mountain View School District who qualified for Supplemental Education Services under the NCLB Act

2007-2009 Corp Member, Jumpstart
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HONORS AND AWARDS

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2012 University of California Evaluation Center (UCEC) Fellow
2010-2012 UC Irvine Department of Education Travel Awards

NATIONAL SERVICE

Ad Hoc Reviewer

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2013, 2014	Journal of Early Adolescence
2011, 2014	Developmental Psychology

Conference Proposal Reviewer

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UNIVERSITY SERVICE (UC Irvine)

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2013	Ph.D. Student Representative, Learning & Cognition Faculty Search Committee
2011-2015	Lab Manager, California Motivation Project Lab
2011, 2012	Welcome Orientation Committee
2011-2012	Lab Manager, Social and Emotional Development Lab
2011	Recruitment Weekend Committee

SCIENTIFIC SOCIETY MEMBERSHIPS

American Education Research Association
American Psychological Association
Society for Research in Child Development

RESEARCH AND STATISTICS SKILLS

Research Methods

Large-scale education field research; field administration of cognitive, achievement, and motivation tests

Analytic Approaches

Ordinary least square (OLS) & logistic regressions, structural equation modeling (SEM), multilevel modeling (such as hierarchical linear modeling, HLM), analysis of variance (ANOVA), item response theory (IRT), multilevel confirmatory factor analysis (MCFA), finite mixture modeling (such as latent class analysis and latent profile analysis, LCA and LPA)

Statistical Software
Stata, Mplus, AMOS, SSPS, flexMIRT, Dedoose

Language
Conversationally fluent in Mandarin Chinese

ABSTRACT OF THE DISSERTATION

Student Perceptions of Classroom Goal Structure:

Methodological Considerations and Person-Context Interactions

By

Arena C. Lam

Doctor of Philosophy in Education

University of California, Irvine, 2015

Jacquelynne S. Eccles, Chair; AnneMarie M. Conley, Co-Chair

One common way used to describe classrooms is by the achievement goals they emphasize and it has been shown that differences in these goals have motivational, behavioral, and achievement implications. This dissertation examines: how to measure the classroom goal structure using student surveys, how perceived goal structure relate to various student outcomes, and whether (mis)alignment between students' and classrooms' achievement goals matters.

Study 1 used multilevel confirmatory factor analysis to determine whether commonly employed measures of classroom goal structure typically verified at the student level (L1) can also be verified at the classroom level (L2). Low intraclass correlation (ICC1) values indicated low proportion of total variance in the classroom goal structure responses explained by student membership in different classrooms. Low ICC2 values indicated low reliability of the classroom aggregate (L2) measures. Although the theorized models of classroom goal structure were acceptable at the individual level, only the performance-avoidance model represented the expected goal structure at the classroom level. Taken together, results cast doubt on whether the L2 classroom goal structure measures can reliably differentiate between classrooms along the classroom goal structure dimensions.

Study 2 tests the matching hypothesis and examines whether the interplay between the classrooms' perceived goal structure and students' personal achievement goals matter for a range of motivational, behavioral, and achievement outcomes. Study 3 is a replication study using another sample of students as well as a longitudinal extension of study 2 by examining long-term consequences measured a year later. To capture students' multiple goals, I employed latent profile analysis to examine the different patterns of students' achievement goals. A series of multiple group structural equation models tested whether classroom goal structures have differential effects depending on students' personal goal profiles. Results provide evidence for the matching hypothesis, wherein students endorsing both mastery and performance-approach goals benefited in higher math grades compared to students who solely endorsed mastery goals, but only in classrooms collectively rated as emphasizing performance-approach goals. However, another finding conflicts with the matching hypothesis. Students endorsing both mastery and performance-approach goals fared worse than mastery-oriented students in classrooms collectively rated as emphasizing performance-approach goals.

CHAPTER 1

Introduction

Student motivation is influenced by the goals individuals have to either *develop* understanding and mastery of content or, in contrast, to *demonstrate* his/her knowledge to others (Dweck & Leggett, 1988). These different goals of either developing or demonstrating competence have implications for cognition (e.g., cognitive engagement), behavior (e.g., use of learning strategies), affect, and academic achievement (for review, see Hulleman, Schrager, Bodmann, & Harackiewicz, 2010). Student motivation is also influenced by the context, something that is sparked by the teacher or the classroom. However, students hold different but strong motivational beliefs and goals before stepping into a classroom for the first time. Person-environment-fit scholars argue that both an individual's characteristics and the classroom context come together to shape psychosocial and academic well-being (Eccles et al., 1993). This interface between the student and the classroom characteristics has implications for student affect, behavior, and learning. This three-study dissertation examines issues related to classroom assessment (Study 1) and whether the interplay, or the fit or misfit, between personal and classroom goals matters for a range of critical student outcomes (Studies 2 and 3).

Broadly, I have two aims in my dissertation. To investigate the role of the socio-emotional climate of the classroom, my first aim is provide insight on the theoretical and methodological considerations when using student surveys to create reliable and valid measures to characterize classrooms. The second aim is to provide insight on how the interplay between students' motivation and the classroom climate can shape individual differences in motivation, affect, strategy use, and learning and the development of these differences over time. I seek to understand whether various patterns of alignment and misalignment between students and classroom characteristics promote or undermine adaptive motivation, help seeking, positive affect, and achievement in mathematics classrooms. Below, I discuss how the three proposed studies meet these two aims using data from a larger study (Conley, 2012).

Study 1

Many researchers in educational psychology use student surveys to assess the classroom environment because: 1) students, who spend much more time in that environment, are better able to provide important information about their classroom than an outsider's one-hour observation can capture, and 2) gathering these data from students is cost effective. Surveys are typically used to measure the shared aspects of the classroom climate that are presumed to be experienced similarly by all students, in addition to students' unique individual experiences. For example in the Patterns of Adaptive Learning Survey (Midgley et al., 2000), students are asked to report on whether or not it is okay to make mistakes in their class—a sentiment that is presumably experienced and perceived similarly by their classmates. Very often in research, individual student reports of the classroom (level 1; L1) are aggregated to create a classroom-level measure (level 2; L2) to provide a more reliable assessment of the classroom climate. However, is this the best way or even a statistically justifiable way?

In the first study of my dissertation, my co-authors and I examined the structure and variability of students' perceptions of the same classroom to investigate how to best measure the classroom climate (Lam, Ruzek, Schenke, Conley, & Karabenick, 2015). Study 1 was designed to answer the question, "Can students' reports of classroom goal structure (L1) be aggregated at the classroom-level (L2) to create a reliable and valid measure of the *shared* classroom climate?" To answer the research question, we employed multilevel confirmatory factor analysis (MCFA; Marsh et al., 2012; Muthén, 1991) using data from 1,406 seventh and 1,822 eighth grade students in 188 mathematics classrooms collected in Spring 2006. We tested whether the reliability and the theorized structure of classroom goal structure hold up at the student level as well as at the classroom level. Study 1's findings speak to the appropriateness of using classroom aggregates of students' reports to capture the *shared* classroom experience and highlight the importance of examining the L2 properties directly before aggregating students' perceptions of the classroom.

Study 2

In the second study, I examined the fit between personal and classroom characteristics using a sample of 2,520 seventh and eighth grade students in 157 mathematics classrooms who were surveyed in the Fall and Spring of the 2005-2006 academic year. My goal in the second study was to examine whether the interplay between the perceived classroom goal structure and students' personal achievement goal orientations matter for students' motivation, help seeking, and mathematics achievement. Congruence of goals is thought to be beneficial—when the affordances of the context match the individual students' goals or strivings. In the second study, I employed a pattern-centered approach (i.e., latent profile analysis or LPA) to examine the interplay between classroom and initial student goals (Fall 2005) in relation to end-of the-year motivation and mathematics achievement (Spring 2006). The findings provide important information about how classrooms work in general, but also whether classrooms work differently for different students.

Study 3

The third study of my dissertation is a replication and extension of study 2. In study 2, I examined the extent of alignment and misalignment between personal and classroom goals within a school year (Fall and Spring of the 2005-2006 academic year). Given the importance of replication studies (Koole & Lakens, 2012), in study 3 I examined the same research questions using a different sample of seventh and eighth grade students from a different year of the larger study (Fall and Spring of the 2004-2005 academic year). In addition, study 3 is a longitudinal extension of study 2 by investigating the long-term consequences of the alignment or misalignment between students' personal goals and their perceived math classrooms' goals by examining outcomes assessed year later (Spring 2006) while controlling for baseline measures (Fall 2004).

Structure of the Dissertation

Each study within the dissertation will be laid out in turn. The study-specific literature will be reviewed, the questions presented, and the methods and results described. Because study 3 is a replication and longitudinal extension of study 2, I described them together in chapter 3 to reduce redundancy. The results are discussed within each chapter and are tied together in a final overarching conclusion discussing the significance of the studies and implications for future research.

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CHAPTER 2

Study 1: Student Perceptions of Classroom Achievement Goal Structure: Is it Appropriate to Aggregate?

A primary goal of education research is to understand the effects of classrooms on student learning and behavior. Accomplishing this goal requires accurately and reliably measuring elements of the classroom environment that are of theoretical and practical interest. These elements include teacher-student interactions, the peer context, and teacher-initiated activities such as instructional practices. A major measurement challenge arises because some features of the classroom are not explicit—such as directly observed utterances or gestures—but rather implicit, embedded in subtle and often information-rich messages teachers communicate to students over an extended period of time (Dorman, 2008). Observation instruments (e.g., the CLASS; Pianta, Hamre, & Mintz, 2012) capture many features of classrooms but may miss implicit instructional practices that drive student learning and behavior (Wagner, Göllner, Helmke, Trautwein, & Lüdtke, 2013). Surveys of students are the primary tool used to assess how students uniquely experience their classrooms (Turner & Meyer, 2000), and from a theoretical perspective, social cognitive theory privileges individuals' construal of their environments. Student reports are commonly used in classroom environment research to measure a variety of constructs, including classroom chaos and social comparison (Marsh et al., 2012), teacher challenge and caring (Morin, Marsh, Nagengast, & Scalas, 2014; Schweig, 2014), and instructional quality (structure of lesson plan, classroom management, understandableness, motivation, student involvement; Wagner et al., 2013), and in the present instance, classroom achievement goal structure (Ames, 1992; Ames & Archer, 1988; Miller & Murdock, 2007).

Such surveys are used to measure *shared* aspects of the classroom environment that are presumed to be experienced similarly by all students as well as each students' unique *individual* experiences. For example in the Patterns of Adaptive Learning Survey (PALS; Midgley et al., 2000), students are asked to report on whether or not it is okay to make mistakes in their class—a sentiment that is presumably experienced and perceived similarly by their classmates. These shared experiences are referred to as elements of the classroom *climate* (Marsh et al., 2012), and survey items that assess climate have the classroom or the teacher as the referent. A closely related but important distinction consists of compositional features such as the percentage of girls in the classroom, which are defined as the classroom *context* (Marsh et al., 2012). In measures of climate, students in the same classroom are assumed to be interchangeable because they are presumably reporting on the same phenomenon, whereas in measures of context, students are not interchangeable (e.g., exchanging a girl for a boy changes the gender context of a classroom).

Research more broadly has focused on definitions of classroom climate that describe the social climate, emotional climate, and motivational climate that students are immersed in (Ames, 1992; Howes, 2000; Moos & Moos, 1978). In the case of the present study, we focus on the classroom's motivational climate, specifically the messages teachers communicate about the purposes or goals of learning that students in the same classroom are similarly exposed to. Classroom achievement goals are key elements of the classroom motivational climate, which is defined in terms of teacher feedback and behaviors that make salient to students particular achievement behaviors that lead to success (Ames, 1992; Ames & Archer, 1988). In this study, we investigate whether classroom goal structures can be appropriately used as measures of a classroom's motivational climate. In prior research on classroom goals, individual student reports (level 1: L1) are often aggregated to create a classroom-level (level 2: L2) measure of the motivational climate when the substantive interest is in the effect of the classroom on student outcomes. However, rarely addressed is whether the classroom goal structure can be considered a valid and reliable measure of climate (i.e., a shared experience) when assessed via individual student reports. Building on initial work by Miller and Murdock (2007), we examine the classroom-level validity and reliability of classroom achievement goals by employing the recently-developed multilevel confirmatory factor analysis (MCFA) method, which assesses whether aggregated student reports capture students' "shared" classroom experiences.

Classroom Goal Structure

Classrooms can be characterized by the types of learning goals teachers emphasize (i.e., classroom goal structure; Ames, 1992). Mastery-focused classrooms are those structured to emphasize understanding the material and learning from mistakes. Performance-focused classes emphasize doing better than others (performance-approach) or avoiding the appearance of being incompetent or less able than others (performance-avoidance). Classrooms are thought be differ along these three goal dimensions and these differences have cognitive, affective, and behavioral implications (for review see Urdan, 2010). Classrooms emphasizing mastery goals are believed to promote adaptive learning outcomes because students are directed towards meaningful, deep understanding (Ames & Archer, 1988; Dweck & Leggett, 1988; Turner, Midgley, Meyer, Gheen, Anderman, & Kang, 2002) and are associated with higher task value, interest, effort, persistence, and intrinsic motivation (Pintrich, 2000; Kaplan & Maehr, 2007). The findings regarding the consequences of performance-oriented classrooms are more variable (see Murayama & Elliot, 2012). For instance, performance-approach classrooms are positively linked with self-efficacy

(Wolters, 2004) but also linked with maladaptive outcomes such as procrastination and lower persistence and intrinsic motivation (Murayama & Elliot, 2009; Wolters, 2004).

Research on classroom goal structure relies almost exclusively on the Patterns of Adaptive Learning Survey (PALS; Midgley et al., 1996, 2000; see Ames & Archer, 1988 and Urdan, 2004 for alternative items assessing classroom goal structure), which was developed to assess student motivation and classroom climate. Although the PALS' *personal* achievement goal scales and *classroom goal structure* scales have been consistently demonstrated to have high validity and reliability when measured at the individual level (for review, see both Meece, Anderman, & Anderman, 2006; Urdan, 2010), considerable uncertainty remains about whether individual student reports of classroom goal structure can be reliably *aggregated* to represent the shared perceptions of classroom achievement goal structure. Single-level confirmatory factor analyses (or "regular" confirmatory factor analysis typically reported in studies) of classroom goal structure scales indicate that they are distinct from personal achievement goal orientations (Wolters, 2004), supporting their validity as constructs separate from personal goals (see Urdan, 2010 for a history and review of extant classroom goal research and the various ways classroom goal structure dimensions has been conceptualized in the literature). However, it remains uncertain whether the proposed three-factor model of classroom goals (mastery, performance-approach, and performance-avoidance) can be presumed a valid measure of the motivational climate at the *classroom level.*

In prior research, performance-approach and performance–avoidance classroom goals are rarely examined in the same study (see Karabenick, 2004 as one exception). Instead, goal structures are dichotomized into mastery and performance, with studies either specifying the performance scale as strictly performance-approach (Kaplan, Gheen, & Midgley, 2004; Wolters, 2004; Shim, Kiefer, & Wang, 2013) or combining approach and avoidance items to create a general performance goal structure scale (Patrick, Kaplan, & Ryan, 2011; Turner et al., 2002). Given the different approaches it is important to determine which of these models can be reliably represented at the classroom level. Accordingly, we test two competing perspectives within the achievement goal theory literature—the mastery perspective and the multiple goals perspective. The mastery perspective conceives all performance goals as maladaptive and is represented by two-factors (mastery and combined performance). The multiple goals perspective acknowledges that although performance-avoidance goals are consistently linked with negative outcomes, it recognizes the potentially adaptive aspects of performance-approach goals such as its association with higher performance (Harackiewicz, Barron, Pintrich, Elliot, & Trash, 2002). Thus, researchers from a multiple goals perspective endorse a trichotomus (three-factor) model that separates the –approach and –avoidance forms of performance orientations (mastery, performance-approach, and performance-avoidance).[1]

Theoretical Assumptions Underlying Classroom Goal Structure Measures

Of concern are the theoretical assumptions and the assessment of classroom goal structure, which is most often treated as a student-level (L1) perceptual measure (e.g., Bong, Woo, & Shin, 2013; Church, Eliot, & Gable, 2001; Ryan & Patrick, 2001; Schwinger & Steinsmeier-Pelster, 2011; Urdan, 2004) and less often as a measure of classroom-level (L2) climate (e.g., Karabenick, 2004; Lau & Nie, 2008; Murayama & Eliot, 2009; Ryan et al., 1998; Wolters, 2004). The decision to use L1 measures versus L2 aggregate measures reflects an

[1] There is empirical support for the 2x2 achievement goal framework for *personal* goals, which uses four-factor scales (mastery-approach, mastery-avoidance, performance-approach, performance-avoidance). However, the mastery-avoidance dimension does not translate as a classroom dimension (Karabenick, 2004) and is not typically examined in classroom goal structure research.

implicit belief about the extent to which a student's perception of classroom goal structures is unique to the individual or a shared classroom experience. The exclusive use of L1 measures implies that classroom goal structure is more appropriately conceived of as a "psychological environment" (Maehr & Midgley, 1991), whereas using L2 measures implies that classroom goal structures are part of a shared classroom climate.

Inconsistent usage of self-reported goal structure as L1 or L2 measures stems from conflicting views and messages about classroom goals in the Achievement Goal Theory (AGT) literature. Ames and Archer (1988) were the first to design and use a student-report measure to assess the salience of mastery and performance goals of the classroom, viewing classroom goals as reflective of each student's construal of the social reality of their classroom (Ames & Archer, 1988, p. 260). Combined with the potential for different experiences in the classroom they are reporting on (e.g., grouping methods and differential teacher behavior), it was assumed that students may also interpret teachers' goal-related messages quite differently from one another due to preexisting differences in students' prior experiences (Ames, 1992).

The theoretical perspective that considers classroom goal structure as a teacher-initiated and shared experience assumes that teachers' goal-related messages are more or less equally applied to all students within the classroom. As noted above, student "reporters" in a classroom are therefore interchangeable. As judges of the same phenomenon, they should tend to agree in their assessment of the classroom goal structure. Thus the use of observational methods for assessing classroom goal structure reflects a perspective that the classroom environment is a measurable shared space (e.g., Meece, 1991; Patrick et al., 2001; Turner et al., 2002; Morin et al., 2014). The decision to treat classroom goal structure as a L1 or L2 measure is not trivial as it reflects what type of "classroom goal structure effects" researchers are interested in.

Methodological Considerations

The common approach to climate assessment consists of aggregating individual student perceptions to provide a more reliable assessment of students' shared experiences of the classroom (e.g., Karabenick, 2004; Lau & Nie, 2008; Murayama & Elliot, 2012; Miller & Murdock, 2007; Ryan et al., 1998; Wolters, 2004). Aggregation controls for variation in students' judgments of the nature and prevalence of instructional practices and other aspects of classroom climate (Miller & Murdock, 2007; Lüdtke, Marsh, Robitzsch, Trautwein, Asparouhov, & Muthén, 2008). When considering classroom climate in this way, reliability and validity of the survey measures cannot be sufficiently assessed at L1 only, and instead must also be assessed at the aggregate (classroom) level given that the phenomenon of interest occurs at L2.

To our knowledge, only two studies on classroom goal structures employed confirmatory factor analysis (CFA) to simultaneously examine the reliability of classroom goal structure at the individual and the classroom level (Miller & Murdock, 2007; Morin et al., 2014). Employing a three-level hierarchical linear measurement model (HLM; individual item responses modeled at L1, within-classroom variation at L2, and between-classroom variation at L3)[2] using PALS' classroom goal structure items, HLM internal consistency results from Miller and Murdock's sample of 689 high school students in 57 classrooms indicated adequate *classroom*-level reliability of classroom mastery (.77) and performance goal structure (.76), the latter of which was a combination of performance-approach and -avoidance items. Morin and colleagues (2014) examined the reliability of students' perceptions of teacher caring, challenge and mastery goal structure (but not performance goal structure) in a sample of 2,541 fourth and fifth grade students in 89 mathematics classrooms. Using MCFA on the PALS items at the student (L1) and

[2] Miller and Murdock's (2007) L2 and L3 correspond to the current study's L1 (student-level or within-classroom variance) and L2 (classroom-level or between-classroom variance).

classroom level (L2), Morin and colleagues (2014) found adequate L2 reliability for the mastery goal structure scale (ICC2 = .85). With the exception of these two studies, all other published classroom achievement goal structure research considers the psychometric properties of these scales at the student-level (using single level CFA). If a researcher's intent is to use classroom goal measures to indicate whether two classrooms have *different* goal structures, then exclusively investigating the measurement properties of the survey instrument at the student level is inadequate (Miller and Murdock, 2007).

Present Study

The present study uses MCFA to determine whether a frequently used student survey of classroom achievement goal structure analyzed at the classroom level fits the a priori structure when classrooms are the unit of analysis. We ask, can student reports of classroom goal structure be aggregated at the classroom-level to create a reliable and valid measure of classroom goal structure? As described above, an initial examination of these issues was carried out by Miller and Murdock (2007). Although Miller and Murdock's methodological approach appropriately measured between-class variability and allowed for the calculation of the reliability of the L1 and L2 intercepts, it remains unclear whether the particular grouping of classroom goal items into two latent constructs (mastery and performance) in that study is the *optimal* way to conceptualize classroom goal structure as a measure of classroom climate. Furthermore, their analysis assumed that items loaded equally onto L2 latent constructs, which is common in goal structure research, but may not represent the actual contribution of each item at L2.

Accordingly, the present study builds on Miller & Murdock (2007) and Morin et al. (2014) by employing MCFA (Lüdtke et al., 2008; Marsh et al., 2012) on the whole AGT framework and testing various theorized classroom goal structure models. Specifically, we assess the L2 reliability and validity of student reports of classroom goal structure in middle school mathematics classes by modeling the various ways classroom goal structure could be configured at L2 (e.g., the trichotomous model vs. mastery + combined performance model). We would like to emphasize that the purpose of our study is not to test one factor structure versus another, but rather to provide evidence of L2 reliability and validity; therefore we present all combinations of factor structures that are available to us. Establishing reliability and construct validity of these measures at the classroom level (L2) is critical for the use of student reports to describe the motivational climate of classrooms.

Methods

Participants and Procedure

Data were obtained from a study of academic motivation and students' perceptions of their mathematics classrooms in the fall and spring of two school years (2004-2005 and 2005-2006). For the current study, we examined student responses from the spring semester of the second year (2005-2006) of the project. Students completed questionnaires in their mathematics classrooms. The sample consists of 1,410 seventh and 1,878 eighth grade students (total N = 3,288) from 188 mathematics classrooms taught by 46 teachers in nine schools in Southern California. We limited the sample to students in classrooms with at least six students who answered the classroom goal structure items to ensure that there are a sufficient number of students per classroom to test the reliability of the aggregate measures (Lüdtke et al., 2008; Miller & Murdock, 2007) as well as to students who responded to at least one item for each of the three classroom goal structure scales described below. Because the study focused on students in middle school where teachers specialize in a content area, each teacher taught multiple classrooms (six on average). Classroom size in this sample ranged from six to 28 students (mean

= 18 students; SD = 5.22). Approximately 5.5% of the sample was in classrooms with 10 students or less.[3] Approximately half of the student sample consisted of males (48%). The majority of students was Hispanic (69%; with the remaining ethnicities being 12% Vietnamese, 9% White, and 10% other), eligible for free or reduced lunch (a proxy for socioeconomic status; 58%), and classified as English Language Learners (42%).[4]

Measures

Classroom goal structure. Classroom goal structures were assessed via student self-report items from the Patterns of Adaptive Learning Scale (PALS; Midgley et al., 2000). All items started with them stem, "In our math classroom…" and were presented along a 5-point Likert scale (1 = Not at all true; 5 = Very true). Mastery, performance-approach, and performance-avoidance goal structure were each assessed using 5 items, totaling in 15 items. Table 2.1 presents exact item wording and descriptive data on the items, including item-level intraclass correlations, means, and standard deviations as well as reliability coefficients for the overall scales. Overall, the scales demonstrate adequate internal reliability (α = .84-.86). A single-level confirmatory factor analysis testing the three classroom goal structure latent factors fit the data ($\chi^2 = 1021.80$, $df = 87$, $p < .001$; CFI = .94; TLI = 0.93; RMSEA = .06, SRMR = .07).

{INSERT TABLE 2.1 HERE}

Prior research has established that classroom goal structures and personal goal orientations represent distinct underlying constructs (Midgley et al., 1998; Wolters, 2004). This

[3] There were very few occurrences of students being in classrooms with 10 or fewer students (5.5% of the sample). We also conducted our analyses on a limited sample of classrooms with 10 or more students (18 classrooms dropped) and obtained similar findings with a negligible improvement in model fit.
[4] Due to the demographics of the schools, extra care was taken during data collection to ensure all students were able to understand and answer the survey. For students who needed Spanish versions of the survey, trained bilingual research assistants read a translated version of the questionnaire aloud as the students followed along the English version of the questionnaire.

study tests this assumption with this sample of middle school students by conducting confirmatory factor analysis with classroom goal structure and personal achievement orientation items from the PALS (mastery, performance-approach, and performance-avoidance). The model included 30 items, with five items loading onto six latent factors and the six latent factors allowed to correlate with one another. The model fit indices indicated that this model represented an adequate fit to the data ($\chi^2 = 2207.46$, $df = 390$, $p < .001$; CFI = 0.95, TLI = 0.94, RMSEA = 0.04; SRMR = 0.05).

Mathematics achievement. Students' concurrent mathematics achievement was examined to assess convergent and divergent validity of the classroom goal structure scales (described further under the Analysis Plan section). Test scores from the California Standards Test (CST) obtained from the school districts' annual testing records constituted the standardized measure of mathematics achievement. Students took the CST in May, approximately a month before the school year ended. CST scaled scores range from 150 to 600, with the cutoff proficiency of 350.

Statistical Modeling

We use multiple measures to assess classroom goal structure's L2 reliability and validity: ICC1, ICC2, $r_{WG(J)}$, and MCFA. Details on the unique information that each statistical test provides are described below.

Assessing within-group agreement and group-level reliability of student surveys. Intraclass correlations (ICC) are used to understand the agreement among students in the same classroom on the construct of interest and therefore can be used as an important measure of the interrater agreement of the construct. Studies employing multilevel modeling report the ICC1 of measured scales to indicate the extent to which variance in individual-level responses can be explained by a higher-level group variable (e.g., classroom). Typically, between-classroom variation in students' perceptions of the classroom goal structure accounts for 15% or less of the total variability in these perceptions (e.g., Ciani, Middleton, Summers, & Sheldon, 2010; Karabenick, 2004; Lau & Nie, 2008; Murayama & Elliot, 2009; Urdan 2004; Wolters, 2004), indicating that classroom goal structure is largely attributable to the individual experiences of the students in the classroom rather than any substantial differences between classrooms.

In addition to reporting intraclass correlations (ICC1), or the agreement between pairs of students within the same class, it is also appropriate to calculate the intraclass correlation at the classroom level (ICC2) to evaluate the reliability of the group average (Lüdtke et al., 2008; Marsh et al., 2012). Put differently, whereas ICC1 indicate the extent to which variance is attributable to group differences, ICC2 assesses the reliability of group-level means, indicating how reliably the aggregate mean rating distinguishes between groups (Bliese, 2000). Though studies often report Cronbach's alpha to evaluate the internal reliability or the average agreement among the items before they are aggregated to form a score, ICC2 is the appropriate indicator of reliability at L2 because Cronbach's alpha does not take into account the nested nature of the data (Miller & Murdock, 2007). ICC2 is interpreted similarly as other reliability measures, is compared against the same standards (acceptable value of 0.7 or higher; Kline, 2000), and measures the agreement between students rather than the agreement between items (Morin et al., 2014). Though studies employing multilevel modeling report the ICC1 of classroom goal structure scales, ICC2 is rarely provided. One drawback of using ICC2 as a measure of reliability is its sensitivity the number of students within each L2 unit and the ICC1. Given the formula for calculating ICC2:

$$\text{ICC2} = \tau_{\xi}^{2}/(\tau_{\xi}^{2} + \sigma_{\xi}^{2}/n_j),$$

where τ_{ξ}^2 is the between-group variance, σ_{ξ}^2 is the within-group variance, and is n_j the average size of the groups (Morin et al., 2014), the higher ICC1 is or the larger the number of students of students sampled per L2 unit, the higher ICC2 is. Thus, a modest ICC1 can result in a high ICC2 if there are enough students sampled at level 2. A more comprehensive assessment of L2 reliability comes from multilevel confirmatory factor analysis (MCFA).

Another way researchers have assessed within-group agreement among respondents is using $r_{WG(J)}$, which compares the observed within-group variance to an expected variance of no agreement under the null hypothesis (James, Demaree, & Wolf, 1984). Similar to ICC, it is an index of interrater agreement used to determine whether there is sufficient agreement among responses to represent a group; however, it estimates interrater reliability while controlling for response bias. The $r_{WG(J)}$ is typically calculated under the assumption that the response bias is equally distributed across the Likert response set (e.g., equally distributed across the five possible responses for an item presented along a 5-point Likert response scale). Specifically, $r_{WG(J)}$ values of .70 or higher is typically used as the criteria for acceptable agreement.

Multilevel confirmatory factor analysis (MCFA). Multilevel factor analytic techniques (e.g., MCFA) have been applied to model survey data obtained from individual students about their classroom's climate to better account for measurement and sampling error (Lüdtke et al., 2008; Marsh et al., 2012; Schweig, 2014; Wagner et al., 2013). Here we apply MCFA to simultaneously examine the structure and reliability of student reports of classroom goal structures at both the individual *and* classroom level.

Whereas multilevel modeling addresses sampling error associated with nested data structures, confirmatory factor analysis is used to address measurement error when assessing relations between observed variables and latent constructs. Muthén (1991) proposed that these two methods can be simultaneously employed using MCFA for the analysis of student reports of their classroom environments. MCFA is also referred to as a doubly latent model (Lüdtke et al., 2008; Marsh et al., 2012) because it is latent in correcting for measurement error both at L1 and L2 (as in traditional factor analysis) and latent in relation to sampling error to account for the number of students sampled in L2 units (as in traditional multilevel methods). In sum, MCFA models simultaneously consider L1 individual student and L2 classroom constructs and can be used to: (a) evaluate the factor structure of L1 and L2 constructs, (b) control measurement error at L1 and L2, (c) control sampling error in the aggregation of L1 responses to form L2 constructs, and (d) provide guidelines for the appropriate analysis of classroom climate as a L2 construct. As a consequence, MCFA examines whether individual student reports can be reliably pooled to provide information regarding the overall, or shared, classroom climate, thereby addressing the appropriateness of using classroom aggregates to measure aspects of classroom climate.

Analysis Plan

To assess L2 model fit and reliability of classroom goal structure, we first estimated the proportion of total variance explained by student membership in different classrooms (i.e., ICC) for each of the classroom goal items (Table 2.1). Sufficient group-level variability is a necessary precondition for conducting MCFA. ICC values should ideally meet or exceed .10 (Wagner et al., 2013), but in practice, multilevel modeling procedures can be used when ICCs are as low as .05 (Dyer, Hanges, & Hall, 2005). Next, we calculated ICC2 to evaluate the L2 reliability of the classroom aggregate measures of classroom goal structure. We then calculated $r_{WG(J)}$ to evaluate within-group agreement along the classroom goal structure scales after correcting for response bias. We examined correlations between student- and classroom-level measures of classroom goal structure and achievement as indicators of convergent and divergent validity. Informed by prior research (for review, see both Meece et al., 2006; Urdan, 2010), we expected mastery goal structure to be positively associated with achievement, performance-approach goal structure to be either positively or negatively associated due to mixed findings (Linnenbrink, 2005), and performance-avoidance goal structure to be negatively associated with achievement.

We then conducted four separate MCFAs on each dimension of classroom goal structure in isolation—mastery (Model 1 or M1 in Table 2.3), performance-approach (M2), performance-avoidance (M3), combined performance (M4)—to examine loading patterns and model fit of each construct both *within student reporters* (L1) and *between classrooms* of student reporters (L2). In the second step, we tested four models to examine model fit of various 2-factor solutions for classroom goals at L1 and L2: mastery + performance-approach (M5), mastery + performance-avoidance (M6), performance-approach + performance-avoidance (M7), mastery + combined performance (M8). As shown in Figure 2.1, we configured the CFA similarly at L1 and L2 to determine whether the same indicators are related to the theoretically equivalent latent variables at both levels (Wagner et al., 2012). We compared fit indices for L1 and L2 versions of the MCFAs using the standardized root-mean-square residual (SRMR)—a level-specific absolute fit index with a proposed cutoff value of .08 in single level models (Hu & Bentler, 1999; Wagner et al., 2013). If classroom goal items fit the a priori structure specified at L2, we would expect a similarly good fit of the model at both levels. Lastly, we tested the trichotomous framework of classroom goal structure (mastery + performance-approach + performance-avoidance; M9).

{INSERT FIGURE 2.1 HERE}

All analyses were conducted in *Mplus 7.2* (Muthén & Muthén, 1998-2012) using a robust maximum likelihood estimator (MLR), which provides estimates of standard errors and chi-square test statistic that are robust to non-normality and non-independence of observations when accounting for the nested nature of data. Because each teacher instructed multiple mathematics classrooms, we modeled the student- and classroom-level variation at L1 and L2 using MCFA and the TYPE= TWOLEVEL COMPLEX estimation function, which adjusts the standard errors and chi-square model fit indices for the three layers of nesting (students within classrooms within teachers). This approach to modeling is based on theory and extant literature, which conceptualizes classroom goal structure as an aspect of classroom climate and our PALS' goal structure items begin with the stem, "In my classroom…" rather than "My math teacher…". Accordingly, the confirmatory factor analyses on the classroom goal structure items were simultaneously modeled at the student and classroom level only (L1 and L2) while the chi-square and standard errors were corrected at the teacher level (L3) to account for the three layers of nesting.

Results

Table 2.1 provides the means and standard deviations for each item and for the three classroom goal structure scales. On average, students rated their classrooms high on mastery (3.87 out of 5), and low on performance-approach (2.14) and performance-avoidance goal structures (1.99). In general, then, students viewed their classrooms as more mastery-oriented than performance-oriented. The distribution of these scales was negatively skewed for mastery goal structure and positively skewed for performance-approach and performance-avoidance. It is noteworthy that *Mplus*' robust maximum likelihood estimator has been shown to be able to handle estimating latent variable models with non-normally distributed continuous items (Beauducel & Herzberg, 2006). Other studies have found similar results given the relative means and standard deviations of their measures (e.g., Ciani et al., 2010; Patrick et al., 2011; Urdan et al., 1998).

The proportion of between-level variance of the total variance (ICC) in each of the classroom goal items is also provided in the first column of Table 2.1. The ICCs were calculated accounting for the three levels of nesting in the data (students within classrooms within teachers). At the classroom level, the ICC for the mastery goal scale is the highest, with 11% of the variance attributable to classroom membership. The performance-approach and performance-avoidance latent factors have a smaller portion of their variance at the classroom level: about 5% for performance-approach and 6% for performance-avoidance. The ICCs in this sample are lower than those reported in other MCFA studies (e.g., Morin et al., 2014; den Brok, Brekelmans, & Wubbels, 2006; Wagner et al., 2013); however, compared to ICCs reported in classroom goal structure studies using traditional hierarchical linear modeling, our ICCs are similar (Ciani et al., 2010; Karabenick, 2004; Lau & Nie, 2008; Murayama & Elliot, 2009; Urdan, 2004; Wolters, 2004). The ICCs of the goal structure items at the teacher level were lower than the ICCs found at the classroom level (mastery goal = .09; performance-approach = .04; performance-avoidance = .04), suggesting that perceptions of students within the same classroom are more similar to one another than perceptions of students who have the same teacher regardless of which classroom they are in.

Group-level reliability, measured via ICC2, was .69 for mastery goal structure, .46 for performance-approach goal structure, and .54 for performance-avoidance goal structure at the classroom level. The ICC2 for the goal structure scales at the teacher level were .88, .73, and .73 for mastery, performance-approach, and performance-avoidance goal structure, respectively. Though the ICC1 values indicated that the classroom accounted for more variance than the teacher level, the ICC2 at the teacher level is much higher than at the classroom level, because ICC2 values are strongly influenced by the average number of students within each higher-level unit (classroom or teacher). In this sample, teachers on average taught 72 students while each classroom averaged 18 students, and this difference substantially inflated the teacher-level ICC2 despite the fact that the teacher-level ICC1 values were *lower* than the classroom-level ICC1s.

The $r_{WG(J)}$ was calculated to determine whether there is sufficient agreement among individual responses to represent a group while controlling for response bias. The $r_{WG(J)}$ is typically calculated under the assumption that the response bias is equally distributed across the Likert response set (e.g., equally distributed across the five possible responses for an item presented along a 5-point Likert scale). Under this assumption, the $r_{WG(J)}$ for mastery goal structure scale was .64, performance-approach scale was .56, and performance-avoidance scale was .62. Although .70 is typically used as the cutoff for acceptable $r_{WG(J)}$ values, LeBreth and Senter (2008) suggest that this standard should be used instead: lack of agreement (0-.30), weak agreement (.31-.50), moderate agreement (.51-.70), strong agreement, (.71-.90), and very strong agreement (.91-1.00). In addition,, Biemann, Cole, and Voelpel (2012) have called for researchers to report a range of $r_{WG(J)}$ as best practice guidelines, with the assumption of the response bias being equally distributed as the maximum value of $r_{WG(J)}$, and the $r_{WG(J)}$ calculated under the assumption of response bias being normally distributed across the items' 5-point Likert scale as the minimum value of the range. We do not make any assumptions about the response bias as it is unclear how much of the observed distribution of PALS responses are due to actual perceptions of classroom goal structure versus response bias, thus, we present all possibilities. The range of $r_{WG(J)}$ suggests that the interrater reliability lies somewhere between lack of agreement to moderate agreement on these constructs (mastery = .30-.64; performance-approach = .18-.56; performance-avoidance = .27-.62).

Correlations between standardized mathematics achievement and classroom goal structure scales at the student and classroom level are reported in Table 2.2. At the individual student level, perceptions of mastery goal structure were weakly, negatively associated with perceptions of performance-approach and performance-avoidance goal structure ($r = -.05$, $p < .01$; $r = -.13$, $p < .001$, respectively) but weakly, positively associated with the student's own mathematics achievement ($r = .17$, $p < .001$). Student perceptions of performance-approach and performance-avoidance shared a high correlation ($r = .83$, $p < .001$), indicating that students perceived them as being very similar. Individual student reports of both performance-approach and performance-avoidance shared a weak negative association with mathematics achievement ($r = -.09$, $p < .001$; $r = -.10$, $p < .001$, respectively). As for the classroom-level (L2) measures, classrooms rated by students as being mastery-oriented were typically weakly negatively associated with student ratings of performance-approach and performance-avoidance goal structures ($r = -.19$, $p < .001$; $r = -.27$, $p < .001$, respectively). Shared student perceptions of performance-approach goal structure were highly correlated with shared perceptions of performance-avoidance goal structure ($r = .91$, $p < .001$), suggesting that students collectively perceived the two performance goal structures as the same. Classrooms viewed by students as being mastery-oriented were moderately associated with classroom-average mathematics achievement ($r = .47$, $p < .001$); in contrast, classrooms perceived by students as being performance-approach or –avoidance oriented were negatively associated with classroom-average achievement ($r = -.13$, $p < .001$; $r = -.19$, $p < .001$, respectively). In sum, the nature of these correlations was as expected and provide some evidence for convergent and divergent validity for the L1 and L2 measures of classroom goal structure.

{INSERT TABLE 2.2 HERE}

Single-factor MCFAs

We first conducted MCFAs on each dimension of classroom goal structure separately to examine how each construct fit at L1 and L2 by itself (Models 1-4 in Table 2.3). We conducted MCFA with the mastery goal structure items only (Model 1) to first assess whether an acceptable fit was possible at the classroom level from the individual student reports. As suggested by Wagner and colleagues (2013), factor loadings, intercepts, and means were freely estimated at both levels while residual variances of the latent factors at both levels were constrained to unity or 1. The freely estimated model should allow for the best fit to the data given the proposed factor structure. A summary of all MCFA results is presented in Table 2.3. Standardized factor loadings at the within-level ranged from .54 to .80, and from .98 to 1 at the between-level (Model 1). Higher standardized loadings at the between level relative to within -level loadings is common in MCFA, due in part to accumulating measurement error at the individual level (Hox, 2010).

{INSERT TABLE 2.3 HERE}

Model fit indices were compared to cutoff values indicating good model fit (Hu & Bentler, 1999): model chi-square (χ^2) with a *p*-value greater than .05; comparative fit index (CFI) and Tucker-Lewis Index (TLI) value equal to or greater than .90 and .95 to indicate adequate to excellent fit, respectively; and root mean square error of approximation (RMSEA) equal to or lower than .06 and .08 to indicate adequate to excellent fit, respectively. The information criteria of these models were also examined, specifically: Akaike information criteria (AIC), Bayes information Criteria (BIC), and sample size adjusted Bayesian information criteria (ABIC). Lower information criterion values indicate better fit to the data. The overall model fit to the data was acceptable ($\chi^2 = 201.38$, $df = 3$, $p < .001$; CFI = .97; TLI = .95; RMSEA = .07). At the within-student level, the fit of the model was acceptable ($SRMR_{within} = .03$) while model fit at the between-classroom level ($SRMR_{between} = .10$) was just above the cut-off of 0.08 that is typically used with single-level models (Hu & Bentler, 1999). Though the mastery goal structure scale had a higher ICC and appeared to have promising between-level psychometric properties, student reports of classroom mastery goal structure in this sample could not be used to differentiate between classrooms in the same way as that among students within classes.

Next, we conducted MCFA for performance-approach and performance-avoidance goal structure items separately. For performance-approach goal structure (Model 2), standardized factor loadings at the within level ranged from .61 to .81, and from .98 to 1 at the between level. The overall model fit to the data was acceptable ($\chi^2 = 249.92$, $df = 13$, $p < .001$; CFI = .97; TLI = .95; RMSEA = .07). At the within-student level, the fit of the model was acceptable ($SRMR_{within} = .03$), but model fit at the between-classroom level was poor ($SRMR_{between} = .13$).

As for performance-avoidance goal structure (Model 3), the standardized factor loadings at the within level ranged from .67 to .81, and from .99 to 1 at the between level. The overall model fit to the data was acceptable ($\chi^2 = 278.01$, $df = 13$, $p < .001$; CFI = .96; TLI = .94; RMSEA = .08). The fit of the model was acceptable at both the within-classroom or student level ($SRMR_{within} = .03$) and the between-classroom level ($SRMR_{between} = .07$), suggesting that within this sample, the proposed factor structure of performance-avoidance goal structure fits the data well at both L1 and L2. Note that although the factor structure appeared to fit the present data well, classroom-level reliability of classroom performance-avoidance goals remains poor (ICC2 = .52).

Prior studies representing the mastery perspective create a general performance goal structure scale by combining performance-approach and –avoidance items into one measure (Patrick et al., 2011; Turner et al., 2002); thus, we conducted MCFA on a single latent factor that included all performance-oriented goal structure items and did not differentiate between approach and avoidance (Model 4). The standardized factor loadings ranged from .65-.81 at the within level and .99 to 1 at the between level. The overall model fit of the combined performance latent factor was acceptable (χ^2 = 940.53, *df* = 73, *p* < .001; CFI = .95; TLI = .93; RMSEA = .06). At the within-student level, the fit of the model was good ($SRMR_{within}$ = .04), but between-classroom fit was just above the proposed .08 cutoff ($SRMR_{between}$ = .11).

Two-factor MCFAs

Next, we conducted four separate MCFA with two latent goal structure factors in Models 5-8 (mastery + performance-approach, mastery + performance-avoidance, performance-approach + performance-avoidance; mastery + combined performance), allowing for the simultaneous evaluation of L1 and L2 factor structure. We believe this is useful to investigate, as it is common for studies to examine only two dimensions of classroom goal structure (mastery + performance). Similarly as before, for all the two-factor MCFA models, factor loadings, intercepts, and means were freely estimated at both levels while residual variances of the latent factors at both levels were constrained to unity or 1 to allow for the best fit to the data given the proposed factor structure. In addition, all models allowed latent variables to freely covary.

Mastery and Performance-Approach Goal Structure. We fit the two-level CFA model shown in Figure 2.1 to the student-reported data. Standardized factor loadings at the within level ranged from .53 to .81, and from .99 to 1 at the between level (Model 5 in Table 2.3). The overall model fit to the data was acceptable (χ^2 = 859.11, *df* = 73, *p* < .001; CFI = .94; TLI = .93; RMSEA = .06). At the within-student level, the fit of the model was similarly acceptable ($SRMR_{within}$ = .07), indicating that students report classroom mastery and performance-approach goals as distinct constructs best represented by two latent constructs. Model fit at the between-classroom level was poor ($SRMR_{between}$ = .48) and did not meet the .08 cut-off that is typically used with single-level models, indicating that student reports of classroom mastery and performance-approach structures in this sample cannot be used to differentiate between classrooms along these two dimensions.

Mastery and Performance-Avoidance Goal Structure. We also employed MCFA with a model including mastery goal structure and performance-avoidance goal structure (Model 6). Standardized factor loadings at the within level ranged from .54 to .80 and from .99 to 1 at the between level. The overall model fit to the data was acceptable (χ^2 = 1044.05, *df* = 73, *p* < .001; CFI = .91; TLI = .91; RMSEA = .06). At the within-student level, the fit of the model was similarly acceptable ($SRMR_{within}$ = .08), indicating that students report classroom mastery and performance-approach goals as two distinct constructs. However, model fit at the between-classroom level was poor ($SRMR_{between}$ = .43), indicating that student reports of mastery and performance-avoidance goal structure did not fit the a priori structure at L2.

Performance-Approach and Performance-Avoidance Goal Structure. We conducted MCFA with a model including the two latent factors, performance-approach and performance-avoidance (Model 7). Standardized factor loadings at the within level ranged from .65 to .82 and from .99 to 1 at the between level. The overall model fit to the data was acceptable (χ^2 = 955.97, *df* = 73, *p* < .001; CFI = .94; TLI = .94; RMSEA = .06). At the within-student level, the fit of the model was similarly acceptable ($SRMR_{within}$ = .04). The model fit at the between-classroom level was close to but above the proposed .08 cutoff ($SRMR_{between}$ = .12), indicating that student reports of performance-approach and performance-avoidance goal structure did not fit the a priori structure at L2.

Mastery and Combined Performance Goal Structure. For the last two-scale MCFA (Model 8), we examined two latent factors: mastery goal structure and an overall performance goal structure which included both performance-approach and performance-avoidance items (the similar model in Miller & Murdock, 2007). Standardized factor loadings ranged from .53 to .81 at the within level and from .98 to 1 at the between level. As Table 2.3 indicates, the overall fit of the model was acceptable (χ^2 = 1959.81, *df* = 183, $p < .001$; CFI = .93; TLI = .92; RMSEA = .05). At the within-student level, the fit of the model was similarly acceptable ($SRMR_{within}$ = .07); however, model fit at the between-classroom level was poor ($SRMR_{between}$ = .44).

Trichotomous Model MCFA

Finally, we employed MCFA with a model representing the trichotomous goal framework (mastery + performance-approach + performance-avoidance goal structure), and the findings from this MCFA (Model 9) point to the same conclusion as in the two-factor solutions. The overall model fit to the data was acceptable (χ^2 = 1935.77, *df* = 181, $p < .001$; CFI = .93; TLI = .92; RMSEA = .05). The factor structure and model fit of the latent factors were acceptable at the student level ($SRMR_{within}$ = .07); however, the model fit was not near the acceptable range at the classroom level ($SRMR_{between}$ = .45).

Discussion

The analyses presented here are among the first to use multilevel confirmatory factor analysis to assess the group-level reliability and construct validity of student reports of their mathematics classrooms' achievement goal structures (see also Morin et al., 2014 for a MCFA with classroom mastery goal structure items but not performance goal structure items). Establishing reliability and construct validity of classroom goal structure measures at the classroom level (L2) is a critical step in establishing the construct validity of classroom goal structure as a L2 classroom climate measure and as a shared classroom phenomenon. Students were individually able (i.e., at L1) to differentiate between the three dimensions of classroom goal structure. However, with the exception of the model solely examining performance-avoidance goal structure, we could not obtain acceptable model fit between classrooms, suggesting that it is not appropriate to aggregate student accounts of classroom goal structure at the classroom level in the present sample. The finding of poor L2 fit suggests that measures of mastery and performance-approach classroom goal structure reflect variability that is more a function of individual differences of students within a classroom than differences between classrooms.

It is noteworthy that obtaining adequate model fit at the student level but poor fit at the classroom level is not uncommon in classroom measurement research (e.g., Stuhlman, Downer, Schweig, & Martinez, 2013). We found adequate fit at the classroom level for the performance-avoidance dimension of classroom goal structure, highlighting the possibility that students within the same classroom are able to agree on the performance-avoidance climate of the classroom and that this particular construct may be used in isolation to differentiate between classrooms. Put together with Karabenick's (2004) finding of adequate between-classroom variation for performance-avoidance goal structure, performance-avoidance appears to be a potentially useful classroom climate construct demonstrating adequate L2 reliability and validity.

Additionally, the ICCs of the classroom goal structure scales reported in this study as well as in others (e.g., Ciani et al., 2010; Karabenick, 2004; Lau & Nie, 2008; Murayama & Elliot, 2009; Urdan, 2004; Wolters, 2004) indicate a lack of substantial agreement within classrooms. However, some studies find higher between-classroom variation for classroom goal structure (Miller & Murdock, 2007; Ryan, Gheen, & Midgley, 1998; Turner et al., 2002). These mixed findings in the literature underscore the importance of examining ICCs to evaluate whether it is appropriate to aggregate student perceptions of the classroom. We believe that it is critical for future research on classroom goal structure to employ MCFA to examine classroom goal structure as a student-level and classroom-level construct and to account for measurement error at the classroom level as in Morin and colleagues (2014). The present study, which is the first to use MCFA on the full suite of classroom goal structure items, highlights the need for replication in future classroom goal structure research and in analyses of purported L2 climate measures since the observed group average may be an unreliable measure and can lead to biased estimates of contextual effects (Lüdtke et al., 2008; Shin & Raudenbush, 2010).

We present three potential reasons for why limited agreement and poor fit were found at the classroom level. These explanations range from teacher-centered explanations to student-centered ones. First, there may be a disconnect between the messages that teachers say in their classroom about the learning goals and the instructional moves and teaching policies teachers act upon (Patrick, Turner, Meyer, & Midgley, 2003). For instance, it could be that different climates coexist in a classroom, and if a teacher signals both mastery and performance criteria of success at the same time, students may pick up on different aspects of these messages. A second explanation is differential teacher treatment of students. For example, teachers directly or indirectly express different expectations through differential attention, grouping and task decisions, and the manner in which instructional practices are carried out (Brophy, 1985; Marshall & Weinstein, 1986). Students in the same classroom may experience these different motivational climates and report on those. A third explanation is that students' personal characteristics color their perceptions of the classroom. For example, Ames (1992) proposed that individuals' past experiences and personal motivational beliefs can influence their perceptions and may explain the high within-classroom variance in perceptions of classroom goal structure. Future research in these areas using multiple methods such as student reports, observations of the classroom, and teacher reports could be used to further investigate these hypotheses and further understand what is associated with heterogeneity in students' perceptions of their classrooms.

Implications for classroom measurement include the need for a deeper understanding of students' cognitive processes as they answer survey questions and reflect on goal-related messages and interactions (Karabenick et al., 2007; Koskey, Karabenick, Woolley, Bonney, & Dever, 2010). Urdan's (2004) interviews with students suggested they were more attuned to the instrumental goals given for doing or engaging in a task rather than any explicit motivational goal provided by the teacher. Further complicating matters, teachers infrequently communicated *why* it was important to engage in a task, and when they did, their reasons were not consistently addressed to one particular motivational orientation (e.g., mastery or performance). Urdan, Kneisel and Mason (1999) also found that elementary students often did not interpret teacher behaviors in ways consistent with achievement goal theory. For example, when asked about how the teacher acknowledged some students for high achievement but acknowledged other students for simple behaviors such as helping clean the classroom, students responded positively to all types of teacher recognition and did not interpret them as conveying differences in ability. Further work is necessary to understand how students interpret teachers' motivational messages and instructional interactions and under what conditions they internalize these messages and interactions (Turner & Meyer, 2000; Urdan & Schoenfelter, 2006). Though underway in other areas of classroom research (e.g., autonomy support; McHugh, Horner, Colditz, & Wallace, 2013), additional research is needed on classroom goal structures.

In addition to trying to piece together a motivational climate measure from individual student reports, one could identify different profiles of student-reported classroom goal structures (e.g., latent profile analysis) within classrooms. Clustering approaches and finite mixture modeling allow researchers to represent classrooms as complex environments in which subgroups of students have differing motivational orientations (Conley, 2012; Karabenick, 2003; Pulkka & Niemivirta, 2013) or differing perceptions of the classroom. Because the current study found that individual reports of the classroom goal structure could not be reliably aggregated (with the exception of performance-avoidance), identifying subgroups of students with similar patterns of perceptions may allow researchers to preserve the practical use of and tap into the inherent strengths of administering student surveys to understand classroom climate. These methods allow for classroom perceptions that are not universally shared and do not rely solely on mean estimation to differentiate between classrooms. For example, the classroom aggregate score for mastery goal structure may not represent many students' experiences in the classroom, due to factors such as differential teacher behavior as well as personal differences in student history and expectations (Ames, 1992). By describing the various profiles of student perceptions that are present in the classroom through the use of clustering approaches and latent profile analysis, a more descriptive and ecologically valid understanding of classroom motivational climates is possible.

A strength of the current study is the large sample of classrooms with many students sampled within each classroom, which are ideal when employing MCFA. Our sampling procedure resulted in three levels of nesting (students nested within classrooms nested within teachers), with teachers instructing six classes on average. Our models accounted for the three levels of nesting by modeling the measurement model at L1 and L2 and correcting the standard errors at L3. We tested the measurement model at student level and classroom level because the items asked students to report on their classroom climate rather than teacher (i.e., using the stem, "In my math classroom…"). Indeed, a study by Turner, Gray, Anderman, Dawson and Anderman (2013) conducted analyses using items with the stem, "My teacher…" as well as items with the stem, "In my classroom…" and found identical results between both scales. Nonetheless, we felt it was important to account for each of the teacher's classrooms as separate clusters because students within each classroom are unique since is it possible that the teacher may alter his/her goal-related messages from class to class. It would be ideal to run a 3-level measurement model with classroom goal structure modeled simultaneously at student, classroom, and teacher level; however, a three-level confirmatory factor analysis cannot be tested given the current existing statistical software.

The current study conducted MCFA on goal structure scales from the Patterns of Adaptive Learning Survey (PALS; Midgley et al., 2000). PALS has been shown to be reliable and valid at the student level in many studies and continues to be the prominent measure used in classroom goal structure research. However, the current study only examined this one measure of goal structure and not alternative ones used in prior research (e.g., Ames & Archer, 1988; Urdan, 2004). We encourage future research using or developing alternative classroom goal structure survey scales to employ MCFA to test the L2 properties and assess the instruments as a climate scales.

It is also worth noting that our sample is highly diverse (69% Hispanic, 14% Vietnamese, 10% White; 58% eligible for free or reduced lunch; 42% classified as English Language Learners) and contains a larger percentage of Hispanic students in comparison to the average California public school for the same academic year (48% Hispanic, 8% Asian, 30% White; California Department of Education, 2006). The diversity of our sample is both a strength and limitation. On one hand, our sample reflects the fact that underrepresented ethnic minorities make up the fastest growing group in the U.S. population (U.S. Census Bureau, 2009). On the other hand, it is unknown the extent our findings based on student perceptions are generalizable to other types of students. It is plausible that some aspects of culture or immigrant generation status might lead Asian and Hispanic students to (a) have differential expectations for the classroom goals, (b) perceive classroom achievement goal structure differently, or (c) respond to these items differently than the traditional samples of White and Black students on which past work has largely been conducted on. It is unclear if perceptions of classroom goals operate similarly across students from different cultural backgrounds. Replication with other samples of students is critical, and we encourage future studies to utilize MCFA to examine the reliability and fit of classroom goal structure group-level means.

Conclusion

Illuminating the reliability and validity of student report measures for characterizing the classroom climate is important not just for motivation research but more generally for teacher effectiveness research. For example, the recent Measures of Effective Teaching Project (Kane & Cantrell, 2010) had students in study teachers' classrooms complete the Tripod student survey instrument, which purports to measure aspects of teacher instruction and classroom climate, and is being used in school districts across the United States as part of teacher evaluation systems. In order for climate measures to be used for such high-stakes purposes, let alone for research purposes, it is essential to know whether the instrument can reliably differentiate between classrooms before estimating its association with aggregate student outcomes. In the present study of highly diverse students in a large number of middle school mathematics classrooms, despite having strong student-level (L1) measurement properties, student-reported classroom goal structure measures were unreliable indicators of the motivational climate of students' classrooms. The fact that these results contradict reliability findings from two other studies that employed similar methodologies (Miller & Murdock, 2007; Morin et al., 2014) highlights the importance of conducting these critical reliability analyses in different samples. Finally, that performance-avoidance was the sole model to adequately fit at L2 contributes to, and is consistent with, the wealth of evidence regarding the increased evaluative focus that accelerates in middle school (Harter, Whitesell, & Kowalski, 1992), which students can apparently discern as a shared experience.

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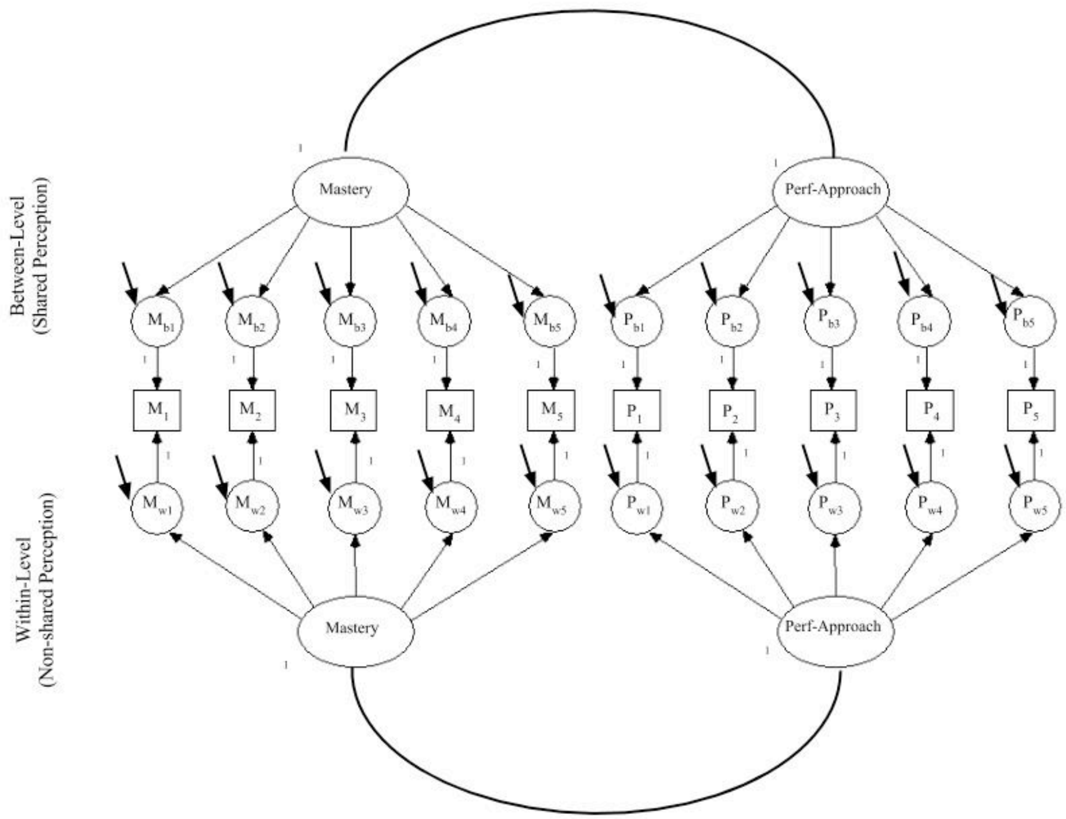

Figure 2.1. *Graphical Model of MCFA.* This figure depicts a multilevel confirmatory factor analysis (MCFA) on scale items associated with two separate latent factors, mastery goal structure and performance-approach goal structure. The same CFA model is simultaneously conducted at the student-level (within-level) and classroom-level (between-level).

Table 2.1

Item-Level Descriptives

	ICC	Mean (SD)
Mastery (α = 0.84)	.11	3.87 (0.93)
In our math class, it's OK to make mistakes as long as you are learning.	.09	4.07 (1.18)
In our math class it's important to understand the work, not just memorize it.	.09	4.00 (1.16)
In our math class, really understanding the material is the main goal.	.09	3.73 (1.26)
In our math class, learning new ideas and concepts is very important.	.07	3.75 (1.16)
In our math class, how much you improve is really important.	.06	3.82 (1.19)
Performance-Approach (α = 0.86)	.05	2.14 (0.99)
In our math class, it's important to get higher scores on tests than other students.	.04	2.28 (1.31)
In our math class, it's important to get more right answers than other students.	.03	1.95 (1.19)
In our math class, getting better grades than other students is the main goal.	.03	2.22 (1.31)
In our math class, it's important to show how smart you are compared to others.	.04	2.00 (1.17)
In our math class, it's important to look like you can do the work.	.04	2.27 (1.22)
Performance-Avoidance (α = 0.85)	.06	1.99 (0.94)
In our math class, it's important that you don't make mistakes in front of everyone.	.04	1.80 (1.12)
In our math class, it's important not to look dumb.	.04	1.94 (1.22)
In our math class, showing others you are not bad in math is really important.	.04	2.09 (1.18)
In our math class, it's important not to do worse than other students.	.04	2.16 (1.24)
In our math class, one of the main goals is to avoid looking like you can't do the work.	.05	1.96 (1.20)

Note. N = 3,288 7th and 8th grade students. All items were on 5-point Likert scale. ICC were calculated at the classroom level.

Table 2.2

Correlations Between Classroom Goal Structure and Standardized Mathematics Achievement

	Student level (L1)				Classroom level (L2)			
	Mastery	P-App.	P-Avd.	Ach.	Mastery	P-App.	P-Avd.	Ach.
Student level (L1)								
Mastery	--							
Performance-Approach	-.05**	--						
Performance-	-.13***	.83***	--					
Achievement	.17***	-.09***	-.10***	--				
Classroom level (L2)								
Mastery	.40***	-.06**	-.09***	.28***	--			
Performance-Approach	-.08***	.32***	.31***	-.08***	-.19***	--		
Performance-	-.11***	.29***	.34***	-.11***	-.27***	.91***	--	
Achievement	.19***	-.04*	-.07***	.59***	.47***	-.13***	-.19***	--

Note. **p* < .05 ***p* < .01 ****p* < .001. *N* = 3,288 students nested within 185 mathematics classrooms. Achievement was measured using scores on the California Standards Test, a state standardized test administered to students annually.

Table 2.3

Summary of MCFA Results for Classroom Goal Structure Items (N = 3,288 students)

	Std. factor loading		Model fit								
	Within	Between	χ^2 (df)***	AIC	BIC	ABIC	CFI	TLI	RMSEA	SRMRw	SRMRb
Single-Factor Models											
1. Mastery	.54-.80	.98-1.00	201.38(13)	46154.04	46288.21	46218.30	.97	.95	.07	.03	0.10
2. Performance-Approach	.61-.81	.98-1.00	249.92(13)	46397.21	46531.37	46461.47	.97	.95	.07	.03	.13
3. Performance-Avoidance	.67-.81	.99-1.00	278.01(13)	46135.34	46269.50	46199.60	.96	.94	.08	.03	.07
4. Combined performance	.65-.81	.99-1.00	940.53(73)	88589.49	88876.12	88726.78	.95	.93	.06	.04	.11
Two-Factor Models											
5. Mastery + Perf-Approach			859.11(73)	92401.87	92688.49	92539.15	.94	.93	.06	.07	.48
Mastery	.53-.80	.99-1.00									
Perf-Approach	.62-.81	.96-1.00									
6. Mastery + Perf-Avoidance			1044.05(73)	92107.06	92393.68	92244.34	.91	.91	.06	.08	.43
Mastery	.54-.80	.99-1.00									
Perf-Avoidance	.68-.80	.99-1.00									
7. Perf-Approach + Perf-Avoidance			955.97(73)	88564.32	88850.95	88701.61	.94	.94	.06	.04	.12
Perf-Approach	.65-.82	.99-1.00									
Perf-Avoidance	.69-.78	.99-1.00									
8. Mastery + Performance			1959.81(183)	134570.50	135009.58	134780.81	.93	.92	.05	.07	.44
Mastery	.53-.80	.99-1.00									
Comined Performance	.66-.81	.98-1.00									
Three-Factor Model											
9. Trichotomous Model			1935.77(181)	134520.84	134972.11	134736.98	.93	.92	.05	.07	.45
Mastery	.54-.80	.99-1.00									
Perf-Approach	.66-.82	.98-1.00									
Perf-Avoidance	.69-.78	.99-1.00									

Note. *** All chi-square test statistics significant at $p < .001$. Students (L1) nested within 185 classrooms (L2) nested within 46 teachers (L3) were taken into account in *Mplus* using TYPE = COMPLEX TWOLEVEL. Although we account for the three levels of nesting, we only modeled the MCFAs at L1 and L2. These models were conducted using MLR estimator. Items were identified as continuous indicators. SRMRw = SRMR within (student-level). SRMRb = SRMR between (classroom-level).

CHAPTER 3

Studies 2 + 3: Does the Alignment Between Students' and Classrooms' Goals Matter? A Latent Profile Approach to Examining Person-Environment Fit

Students enter classrooms with a range of different goals and attitudes about school, and these individual differences have implications for their affect in class and learning (Conley, 2012; Pastor, Barron, Miller, Davis, 2007; Pintrich, 2000; Tuominen-Soini, Salmela-Aro, & Niemivirta, 2008). The challenge is finding a way to engage these different students. The classroom's goal structure plays an influential role in shaping students' affect in class, whether or not they ask for help, the kinds of help they decide to seek, and ultimately their learning (Karabenick, 2004; Linnenbrink, 2005; Ryan, Gheen, & Midgley, 1998; Schenke, Lam, Conley, & Karabenick, 2014; Wolters, 2004). Indeed, how the goals of the classroom interface with students' personal goals can be an important driving influence behind adaptive or maladaptive changes across the school year (Baron & Harackiewicz, 2003; Harackiewicz & Sansone, 2001; Lau & Nie, 2008; Linnenbrink & Pintrich, 2001; Murayama & Elliot, 2009; Wolters, 2004). To date, the alignment between classroom and personal has been tested using 2-way interaction terms, which are helpful to see, for instance, how personal mastery goals interact with classroom performance goals to predict outcomes. However, classrooms and students rarely focus on only one goal. For example, the level of students' personal performance-approach goals in relation to the students' mastery goals matters (Pintrich, 2000; Tuominen-Soini et al., 2008). The alignment between the students' other goals (essentially, a 3-way interaction term) is important to gain a fuller understanding of how real—but difficult to model—multidimensional classrooms interact with student characteristics to affect outcomes.

In Studies 2 and 3 of my dissertation, I examine the joint contributions of classroom and personal goals in relation to a range of motivational (self-efficacy, interest, positive and negative affect), behavioral (help seeking), and learning (end-of-year math course grade and standardized mathematics achievement) outcomes to broadly examine the consequences of goal congruence between the student and learning environment. A specific emphasis of these two studies is the use of latent profile analysis (a pattern-centered approach) for a holistic examination of the naturally occurring configurations of students' personal goals and testing whether the relation between classroom goal structure and the various outcomes differ by these student motivational patterns to investigate the short- and long-term consequences of these different patterns of person-environment fit (Bauer & Shanahan, 2007; Bergman, 2001).

This chapter begins with an overview of achievement goal theory; briefly summarizes the emotional, behavioral, and cognitive consequences of classroom and personal goals; and highlights the conflicting views and findings regarding the consequences of performance-approach goals. Next, I discuss the extant research and the findings associated with the various matches and mismatches that can occur between students' personal goals and the classrooms' goals. Finally, I present limitations of the current methods used to study (mis)matches and propose and illustrate an alternative method to address those limitations.

Achievement Goal Theory

One way to characterize classrooms is by the achievement goals they emphasize (Ames, 1992). According to achievement goal theory, the goal structure of a learning environment influences students' motivation, cognitive engagement, and achievement within that setting (Ames, 1992; Ames & Archer, 1988). Classroom goal structure describes the type of achievement goals emphasized by the classroom instructional practices and policies. For example, teachers can employ teaching strategies and grading policies that emphasize personal growth, learning, and understanding (mastery goal structure) or emphasize performance and relative ability (performance goal structure). In terms of performance-oriented classrooms, classrooms can emphasize the goal of doing better than others (performance-approach) or avoiding the appearance of being incompetent or less able than others (performance-avoidance). The types of tasks assigned, the grading procedures, the degree of autonomy students are provided, and the way students are grouped are thought to embody the perceived classroom goal structure (Ames, 1992; Kaplan, Middleton, Urdan, & Midgley, 2002; Urdan, 1997).

Achievement goal theory is also used to describe individual differences in students' personal achievement goals—the reasons or purposes students engage in academic tasks (Dweck & Leggett, 1988). Students with *personal* mastery goal orientations use internal standards to judge success and focus on personal growth, developing competence, and deepening understanding. In contrast, students with a performance orientation use external standards to judge success. Students characterized by a performance-approach orientation focus on doing better than others and demonstrating their competence. Students characterized by a performance-avoidance orientation focus on avoiding looking incompetent or less able than others. These goals or reasons for why they engage in academic tasks have different cognitive, affect, and behavioral implications (Dweck & Leggett, 1988; Pintrich, 2000; Tuominen-Soini et al., 2008).

In general, achievement goal theorists agree that mastery goals are adaptive and should be promoted at both the student- and classroom-level and that performance-avoidance goals are detrimental and consistently predict negative outcomes (for review, see Hulleman et al., 2010). Personal mastery goals are thought to be highly adaptive for promoting learning outcomes because students are directed towards meaningful, deep understanding (Dweck & Leggett, 1988) and have been linked with higher task value, interest, effort, persistence in students, and intrinsic motivation (Pintrich, 2000).

The point of contention is the consequences of performance-approach goals. The mastery perspective asserts that, although performance-approach goals can be adaptive for some outcomes such as cognitive engagement and achievement (Pintrich, 2000; Wolters, Yu, & Pintrich, 1996), when looking at the student or classroom as a whole, performance-approach goals come at a cost (Lau & Nie, 2008; Midgley, Kaplan, & Middleton, 2001; Murayama & Elliot, 2009; Wolters, 2004). It is thought that if performance-approach students experience any difficulties along the way, there may be costs (e.g., lower interest, negative affect) and students may resort to using maladaptive strategies (e.g., cheating, asking for the correct answer to avoid work) to attain their goal of being better than others (Midgley et al., 2001). In contrast, the multiple goals perspective contends that performance-approach goals are beneficial for cognitive engagement and achievement, so that students or classrooms with a combined emphasis on mastery and performance-approach goals can also be beneficial (Harackiewicz et al., 2002; Linnenbrink, 2005; Murayama & Elliot, 2012; Pintrich, 2000). It is thought that for some students, optimal motivation may come through multiple goal pursuits such that performance-approach goals are adaptive when endorsement of both mastery and performance-goals are high (Linnenbrink, 2005; Muis, Ranellucci, Franco, & Crippen, 2013). For example, students oriented to both mastery and performance-approach goals may succeed in classrooms when normative grading is used. Not only are the students focused on deepening understanding, they are also focused on getting the high grades needed to succeed in a performance-oriented class. In contrast, those coming from a mastery goals perspective would argue that high performance-approach goals can dampen the positive benefits of high mastery goals (Midgley et al., 2001).

Extant research supports both perspectives. Some studies show that performance-approach goals dampen the positive effects of mastery goals; others show that a combined focus on mastery and performance-approach goals has additional benefits compared to purely mastery or purely performance-approach goals (see Senko, Hulleman, & Harackiewicz, 2001). Overall, there is not a clear story in the extant findings. Indeed, Pintrich (2000) suggested that there may be "multiple pathways" to the same desirable outcome. Harackiewicz and colleagues (2002) argued the same—that performance-approach goals are not always maladaptive and that there is not a single "mastery road' all students must take in order to succeed. Rather, performance-approach goals can be adaptive with the caveat that the level of personal performance-approach goals in relation to personal mastery goals matters (Pintrich, 2000). This idea of the "multiple pathways" to success can also be applied to thinking how the students' and classroom's goals come together to shape student success. Applying the revised goals perspective to the classroom level, the level of performance-approach goal structure in relation to the classrooms' mastery goal structure matters for how the classroom goals together affect change.

Match and Mismatch Between Personal and Classroom Goals

Some researchers using achievement goal theory focus only on the classroom goals or only students' personal goals. Other researchers examining classroom and personal goals together have investigated mediation models (e.g., Church et al., 1991; Murayama & Elliot, 2009) in which classrooms' goal structure influence students' personal goals, which in turn, have a more proximal effect on students' outcomes. (Ames, 1992). However, ignoring the possibility of an interactionist effect can lead to misleading conclusions (Murayama & Elliot, 2009). For instance, results from a direct effects model alone can lead to the conclusion that a certain type of classroom goal structure is adaptive because it has a direct positive influence on outcomes.

However, it is possible that this same classroom goal structure dampens the positive influence or exacerbates the negative influence of some personal achievement goals on the same outcomes.

The matching hypothesis (Harackiewicz & Sansone, 1991; Linnenbrink & Pintrich, 2001; Linnenbrink, 2005) can be thought of as an extension of the person-environment fit hypothesis (Eccles et al., 1993a) to achievement goal theory. According to the matching hypothesis it is the fit between person and context that matters; students whose personal goals match the goals espoused by the classroom environment should fare better socioemotionally and academically than students whose personal goals do not match the learning environment's goals.

However, the simple dichotomy of match and mismatch limits our understanding of how personal and classroom goals jointly impact students, because matches can either strengthen desirable or undesirable relations (Lau & Nie, 2008). One example of a match strengthening desirable relation is when classroom mastery goals enhance the desirable effects of personal mastery goals. In contrast, matches can also strengthen undesirable relations. This idea is related to vulnerability-stress hypothesis in psychopathology (Ingram & Luxton, 2005), in which an individuals' personal vulnerability is exacerbated by the level of stress experienced by the individual from his/her environment. In the case of achievement goal theory, a student with high performance-avoidance goals should fare worse in a performance-oriented classroom than in a mastery-oriented classroom. Even still, there is some disagreement about the potential directions of the interactive effects of personal and classroom goals (Linnenbrink & Pintrich, 2001). Advocates of the mastery perspective argue that mastery goals (classroom or personal) always buffers against the negative consequences of students' personal performance goals. In contrast, from a multiple goals perspective, performance goals are not always deleterious, and a match between person and classroom performance goals can be beneficial. For example, a performance-approach oriented student may thrive in a classroom that also emphasizes performance and achievement; however, that same student in a non-performance-oriented classroom may be seen as abrasive to other students and thus suffer in the realm of peer relationships (Harackiewicz & Sansone, 1991).

Mismatches between students' personal goals and classroom goals are thought to *weaken* desirable or undesirable relations. Mismatches can be adaptive by buffering or weakening undesirable relations (the buffering hypothesis). For example, being in an adaptive mastery-oriented classroom can buffer against the negative effects of students' maladaptive performance-avoidance goals (Linnebrink & Pintrich, 2001). Mismatches can also be non-adaptive when they weaken desirable relations. For example, classrooms high in performance-approach goals can weaken the positive relation between students' personal mastery goals and interest in the content.

Experimental studies. The results of experimental studies that assign students into different learning conditions (mastery goal structure, performance goal structure, and sometimes a combined mastery and performance-approach goal structure) to test the matching hypothesis have been mixed. Some found null results (Linnenbrink, 2005); others have found some support for the relation between classroom goals and outcomes being moderated by personal goals (Muis et al., 2013; Newman, 1998). Newman (1998) asked fifth and sixth grade students to solve mathematics problems and randomly assigned them to either a mastery or performance goal condition. In the performance context, personal performance-approach goals were negatively associated with help seeking. In contrast, in the mastery condition, the relation between personal performance-approach goals and help seeking was positive, supporting the buffering hypothesis. In another experiment, Muis and colleagues (2013) assigned 250 freshman university students in a chemistry course into four conditions that provided different types of feedback for the online quizzes required for the course: control (raw score), mastery (improvement over time), performance-approach (normative feedback in the form of a percentile score and showing a curve), and combined mastery and performance-approach condition (both improvement over time and normed feedback). They found that normative feedback (performance-approach structure) benefited everyone. However, the authors also found support for the matching hypothesis, with mastery-oriented students in the mastery condition benefiting in metacognitive self-regulation but not overall course grade.

These experimental studies designed meticulously scripted goal conditions that lacked nuances in the type of feedback given to students. However, real classrooms rarely emphasize a single goal (or a clear combined goal) and the goals and feedback may be more nuanced and sometimes ambiguous. Investigations of real classrooms' naturally occurring goal structures are needed to examine whether multiple goals are adaptive, because this research carries implications regarding the recommended instructional policies and practices and types of classroom climate that are created (Midgley et al., 2001).

Correlational studies. There are a handful of studies that test the matching hypothesis by examining students in real mathematics classrooms (Lau & Nie, 2008; Murayama & Elliot, 2009; Wolters, 2004). These studies used surveys to assess students' personal goals as well as their perceptions of their mathematics classrooms' goal structures. Overall, these studies provide support for the matching hypothesis. For example, in one study mastery-oriented students reported higher effort and metacognitive strategy use in classrooms collectively rated as emphasizing mastery goals (Wolters, 2004). There is also some support for the adaptive consequences of personal performance-approach goals when students are in classrooms that are characterized by the same goals. High school students' personal performance-approach goals were positively linked with intrinsic motivation and academic self-confidence, but only in classrooms that were collectively perceived as emphasizing performance-approach goals (Murayama & Elliot, 2009). However, being in classrooms that emphasize performance-approach goals exacerbated the negative effects of personal performance-avoidance goals on engagement (Lau & Nie, 2008), self-concept (Murayama & Elliot, 2009), metacognitive strategy use (Wolters, 2004), as well as effort withdrawal and avoidance coping (Lau & Nie, 2008). Overwhelmingly, the evidence demonstrates that even if the teachers focus on the approach dimension of performance goal structure, emphasizing performance goals in the classroom exacerbates the risk to performance-avoidant students.

Whereas there is much evidence supporting the matching hypothesis, the findings regarding the consequences of the mismatch between classroom and students' goals are less clear. In support of the mastery goals perspective, Wolters (2004) found that the positive association between personal mastery goals and effort was dampened in classrooms collectively perceived as emphasizing performance-approach goals. Curiously, Murayama and Elliot (2009) found that students' personal performance-approach goals were positively associated with intrinsic motivation in classrooms collectively rated as low mastery, but not in classrooms rated as highly mastery-oriented. The authors proposed one plausible explanation is that students pursuing performance-approach goals in a classroom focused on mastery goals may be viewed as antagonistic or self-centered by others. The discrepant findings highlight the need for more research examining plausible sources of conflicting findings, such as the (mis)matches along more than just two goal dimensions.

Methods for Examining Match Between Person and Environment

The aforementioned studies that examine students in real classrooms (Lau & Nie, 2008; Murayama & Elliot, 2009; Wolters, 2004) aggregated students' reports to the classroom level to create a measure capturing the shared perception of their math classrooms' goal structure, and then tested the matching hypothesis within their hierarchical linear models using 2-way interaction terms between the classroom and personal goal measures (e.g., classroom mastery X personal mastery goals; classroom mastery X personal performance-approach goals). A limitation of these 2-way interactions is that researchers are only able to investigate one pair of interactions at a time. Students and classrooms rarely emphasize only a single goal. For example, when testing the match or mismatch between a classroom's mastery goals and the students' performance-approach goals, the revised goals perspective would argue that the students' relative level of mastery goals also matters in how the student and classroom goals come together. This would require 3-way interaction terms, 4-way interactions terms, and so on in order to fully understand how real—but difficult to model multidimensional classrooms interact with student characteristics to affect outcomes. However, these higher-order interaction terms quickly become difficult to interpret. These higher-order interaction terms also assume that the researcher has the statistical power to detect these effects.

Due to the multidimensional manner to which students are motivated, recent studies advocate the use of clustering or pattern-centered techniques to capture holistic patterns of student motivation (Conley, 2012; Pastor et al., 2007; Peck, Roeser, Zarrett, & Eccles, 2008; Roeser & Peck, 2003; Tuominen-Soini et al., 2008).[5] Pattern-centered approaches are ideal for

[5] Pattern-centered approaches, sometimes referred to as person-centered approaches, include various techniques such as cluster analysis, latent class analysis (LCA uses categorical indicators), latent profile analysis (LPA uses continuous indicators), finite mixture modeling, etc.

modeling complex and non-linear interactions by identifying patterns of values across all variables so that they are viewed holistically as the unit of analysis (Bauer & Shanahan, 2007).[6] Pattern-centered approaches can uncover and display complex relationships in a more natural, easier to understand way through the use of patterns, allowing researchers to represent the different combinations of personal goals as subgroups. An important point of clarification is that variable-centered and pattern-centered approaches are complementary rather than contradictory approaches to studying complex interactions. Bauer and Shanahan (2007) demonstrate that complex interactions can be similarly captured with both pattern-centered approaches and variable-centered approaches through statistically significant higher order interaction terms. However, Bauer and Shanahan (2007) noted that researchers must specifically include and test for these higher-order interaction terms in their models when using variable-centered approaches.

In this study, I use latent profile analysis to preserve the patterns of personal goals as they actually exist within individuals. Using these personal goal profiles, in this study I will use multiple group structural equation modeling to test whether the relation between classroom goals and outcomes are moderated by the students' profile group membership. That is, I will test whether the association between classroom goal structure and the various outcomes is different for students with different personal achievement goals. If the association differs across the student profile groups, then the influence of classroom goals is not the same across the students within this sample and the level of students' personal achievement goals play a role and matter.

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[6] Complex interactions include person-person interactions (various constructs that reside within a person), person-context interactions (e.g., person-environment fit), and context-context interactions (e.g., systems theory's idea that multiple contexts interact to shape individual well-being).

Present Studies (2 + 3)

In studies 2 and 3 of my dissertation, I employ latent profile analysis (LPA) and multiple group structural equation modeling (multigroup SEM) to examine the interplay between the classroom goal structure and seventh and eighth students' personal achievement goal orientation in relation to motivational, behavioral, and achievement outcomes. The outcome measures I examine are similar to those used in prior studies testing the matching hypothesis (Lau & Nie, 2008; Linnenbrink, 2005; Muis et al., 2013; Murayama & Elliot, 2009; Newman, 1998; Wolters, 2004). A broad range of outcomes is needed to understand the various consequences of match and mismatch between personal and classroom goals. Specifically, in both Studies 2 and 3 I seek to answer three research questions:

1. What are the different patterns of students' personal achievement goals (mastery, performance-approach, and performance-avoidance)?
2. How are math classrooms' goal structure (mastery and performance-approach)[7] related to students' motivation (self-efficacy, interest, affect), behavior, (help seeking), and learning (math course grade and standardized achievement)?
3. Do classroom goal structures have differential effects depending on students' personal achievement goal profiles?

Put differently, these two studies estimate the main effect of classroom goals on the various outcomes and then tests whether personal goals, as captured by latent profile groups, moderate these associations. Study 3 is an extension of Study 2 in two ways: 1) by replicating the findings with another sample of students in the data, and 2) by examining the longitudinal consequences

[7] Study 1 found high correlations between performance-approach and performance-avoidance goal structure. Because there is much support for classroom performance-approach goal structure in comparison to performance-avoidance goal struture in the literature, studies 2 and 3 will only focus on performance-approach goal structure.

of match or mismatch between the students' and classroom's goals by following the students into the next school year. Longitudinal data are important to examine the proposed trajectories fostered by different personal and classroom goals. It is not sufficient to examine different outcomes at one time point only. Although it is a conservative approach, it may be that some positive or negative outcomes do not occur until time has allowed for potential goal effects to accumulate. I first discuss Study 2.

Study 2

Participants

Study 2's participants are 2,520 seventh and eighth grade students (1,197 seventh grade students and 1,323 eighth grade students) from 157 mathematics classrooms taught by 41 teachers in seven Southern California middle schools. The average classroom size consisted of 19 students with class sizes ranging from 6 to 30 (SD = 2.31). Student surveys were administered in the Fall and Spring to assess students' perceptions of the math classrooms' goal structure, as well as their personal goal orientation for mathematics and other motivational beliefs for mathematics. Students' scores from the California Standards Test (CST) taken in the Spring were obtained. Only students with valid survey responses from the Fall and Spring and achievement data are included in the analyses.

Measures

The Patterns of Adaptive Learning Survey (PALS; Midgley et al. 2000) was administered in the Fall and Spring of the 2005-2006 academic year to assess students' motivation for mathematics and perception of the classroom goal structure (see Appendix A for full items). All items were presented along a 5-point Likert scale (1 = not at all true; 5 = very true). Descriptives and pairwise correlation coefficients between the measures are provided in Tables 3.1 and 3.2, respectively.

{INSERT TABLES 3.1 & 3.2 HERE}

Personal goal orientation. Three 5-item scales assessed students' personal achievement goals for mathematics: mastery (e.g., "Learning a lot of new things is what is important to me in math"), performance-approach (e.g., "My goal is to do better than other students"), and performance-avoidance (e.g., "My goal is to keep others from thinking that I'm not smart in math") goal orientation. Students' responses for each of the 5-item scales were averaged so that each student received one score for personal mastery, performance-approach, and performance-avoidance goal orientation. The scales demonstrated very good internal reliability across the sample (mastery: $\alpha = 0.87$; performance-approach: $\alpha = 0.87$; performance-avoidance: $\alpha = 0.82$).

Classroom goal structure. Three 5-item scales assessed students' perceptions of their math classrooms' mastery and performance-approach goal structure. All items began with the phrase: "In our math class..." Classroom mastery goal structure was assessed with five items (e.g., "In our math class, it's OK to make mistakes as long as you are learning"). Five items assessed performance-approach goal structure (e.g., "In our math class, it's important to get higher scores on tests than other students"). Students' responses for each of the 5-item scales were averaged so that each student received a score for classroom mastery and performance-approach goal structures. The scales demonstrated good internal reliability across the sample (mastery: $\alpha = 0.79$; performance-approach: $\alpha = 0.87$).

Self-efficacy. Students' self-efficacy beliefs for mathematics were assessed using four items (e.g., "How confident are you that you can do all the work in math class, if you don't give up?") in the Fall and Spring. The response scale for these items was anchored at the endpoints and in the middle with anchors that matched the item (certain, sure, or confident): not at all sure, somewhat sure, very sure. Student responses on these four items were averaged to create a score representing their judgment about their ability and confidence to perform adequately in mathematics (α = 0.79-0.83).

Interest. Interest value for mathematics was assessed using six items adapted from Eccles, Wigfield, and colleagues (Eccles et al., 1993b; see Conley, 2012 for more information on this adapted scale). Student responses on these six items were averaged to create a score representing their interest in mathematics (e.g., “I enjoy doing math.”). Internal consistency was high for the scale (α = .96 for both Fall and Spring).

Affect. Items assessing positive and negative affect in math class were taken from the Positive and Negative Affect Schedule—Expanded Form (PANAS-X; Watson & Clark, 1994). Four items were used to measure positive affect (happy, enthusiastic, excited, interested) in math class (e.g., “How often do you feel happy in your math class?”) Four items measured negative affect (anxious, bored, exhausted, irritated) during mathematics (e.g., How often do you feel anxious in your math class?”). The response was anchored at the endpoints and in the middle with these anchors: never, sometimes, and always. Across both Fall and Spring measures, the internal consistency was higher for positive affect (α = 0.88) than negative affect (α = 0.59-0.60).

Help seeking. Help-seeking items were adapted from Karabenick (2004). Five single-item indicators were used to assess instrumental help seeking, expedient help seeking, seeking help from a teacher, seeking help from a classmate, and avoidant help seeking. Instrumental help seeking (asking for help with the goal to learn and deepen understanding) was measured by asking students, “If I were to ask for help in this math class it would be to learn how to do the problems.” Expedient help seeking (ask for help to avoid effort and work) was measured by asking students, “If I were to ask for help in this math class it would be to quickly get the answers I needed.” Help from a formal source (i.e., teachers) was measured by asking students, “If I didn’t understand something in this math class I would ask my teacher for help.” Peer help seeking was measured by asking students, “If I didn’t understand something in this math class I would ask another student in class for help.” Avoidant help seeking (not asking for help even though there is a perceived need) was measured by the item, “Even if I couldn’t finish an assignment for this math class, I wouldn’t ask for help.” This study used single item indicators to parse out whether students ask for help (avoidant help seeking), and if they do, the types of help they seek (instrumental and expedient) and from whom (peers and teacher).

Mathematics achievement. This study examined how classrooms and students’ personal goals relate to two different measures of mathematics achievement, math course grades and standardized test scores. End-of-the-year math course grades were obtained from school district records. Only whole letter grades were provided (A, B, C, D, F) without plusses or minuses, so a 5-point scale was created (1 = F; 5 = A). The school districts also provided standardized test scores from the California Standards Test (CST), with a possible range of 150 to 600. Students took the CST in May, approximately a month before the school year ended. All seventh grade students took the same test, General Mathematics 7. Students in the eighth grade took different tests depending on the mathematics course they were enrolled in. For this sample, 32% of the eighth grade students took the General Mathematics 8 test, 19% took Algebra 1, and 1% took Geometry. The CST math scores were standardized within math test type (e.g., Algebra 1, Geometry) to take into account that students within the same grade level take different tests.

Covariates. Previous year's mathematics performance on the CST will be included to test for current year changes in standardized performance. Fall student reports will be included to examine current year changes in self-efficacy, interest, affect, and help seeking in the context of mathematics.

Analysis Plan

In general, the analysis plan consists of three steps. I employed: 1) latent profile analysis (LPA) on students' personal achievement goals, 2) SEM to estimate the main effect of L1 and L2 classroom goal structure; and 3) multigroup SEM to test whether the associations between L1 and L2 classroom goal structure and the 11 outcomes varied between specific contrasted student profile groups.

To answer the first research question (What are the different patterns of students' personal achievement goals?), I conducted LPA in *Mplus 6.12* (Muthén & Muthén, 1998-2010) to examine the different patterns of values across the students' incoming personal achievement goals for math scale scores (mastery, performance-approach, and performance-avoidance goals measured in the Fall; Figure 1). I used theory, a suite of model fit indices, and model entropy to choose the final number of profile groups that best fit the data. After finalizing the measurement model for the latent personal goal profiles, I obtained the probability of each individual's membership for each profile to see how individuals fit into these different subgroups of personal achievement goals. I exported these posterior class probabilities from *Mplus 6.12* and merged this information into *Stata 11.2* (StataCorp, 2009) to create a class membership variable so that each individual is linked to his/her highest probability profile group representing different values of personal achievement goals.

{INSERT FIGURE 1 HERE}

Next, I conducted a series of structural equation models to examine the main effects of classroom mastery and performance-approach goal structure assessed in the Fall on the various outcomes of interest assessed in the Spring (Figure 2). These SEMs controlled for students' prior mathematics achievement as well as Fall measures of the outcomes in order to examine how classroom goal structure is associated with over-the-year changes. In addition, the same set of SEMs were conducted using two different measures of classroom goal structure: 1) individual perceptions of classroom goal structure, and 2) shared perceptions of classroom goal structure. The findings from Study 1 of this dissertation suggest that student reports of classroom goal structure should not be aggregated to the classroom level. However, prior studies testing the matching hypothesis have used classroom aggregate measures of classroom goal structure. I conducted the same analyses but using classroom aggregate measures to examine if the findings differ from the student-level models.

{INSERT FIGURE 2 HERE}

Then, I employed multigroup SEM to test whether the associations between L1 and L2 classroom goal structure and the various outcomes differ between differently motivated students. That is, using planned contrasts between two achievement goal profile groups, these multigroup SEMs tested whether the estimated effect of classroom goal structure differs between two differently motivated profile groups. The specific steps in conducting the multigroup SEMs are detailed in the Results section below.

The nested structure of the data with students nested within classrooms was taken into account using TYPE = MIXTURE COMPLEX in *Mplus 6.12*. All analyses were conducted using a robust maximum likelihood estimator (MLR), which provides estimates of standard errors and chi-square statistic that are robust to nonnormality and nonindependence of observations when accounting for the nested nature of data.

Results

Latent Student Achievement Goal Profiles

I examined the Bayes Information Criterion (BIC), Consistent Akaike's Information Criterion (CAIC), Approximate Weight of Evidence Criterion (AWE), Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR), and model entropy to choose the number of different profiles as suggested by the data. Taken together, the fit indices and model entropy suggest the "right" amount of groups where the groups are different from each other, but not too many groups where parsimony is lost and the group differences are not very meaningful. Lower information criterion values (BIC, CAIC, AWE) indicate better fit to the data. The VLMR test is similar to the standard chi-square difference test. Low *p*-values for the VLMR test suggest that the model with one less class should be rejected in favor of the estimated model (Lo, Mendell, & Rubin, 2001). Model entropy values range from 0 to 1 with higher values indicating clearer class separation. As a rule of thumb, values over 0.80 indicate good separation of the latent classes (Celeux & Soromenho, 1996).

The results from a series of LPA suggested that a 6-class solution fit the data best (Table 3.3). The average personal achievement goal scale scores for the six profiles are provided in Table 3.4 and Figure 3.4 provides a visual depiction of the same information. The six groups were labeled as: 1) mastery goals perspective, 2) medium mastery-differentiated, 3) high non-differentiated, 4) revised goal perspective, 5) medium non-differentiated, and 6) low mastery-differentiated.

{INSERT TABLES 3.3 & 3.4 HERE}

{INSERT FIGURE 3.3 HERE}

As Table 3.4 and Figure 3.3 illustrate, the *mastery goals perspective* students (profile 1; 25% of the sample) reported high mastery goals and low performance-approach and –avoidance goals, representing the most adaptive motivational profile as hypothesized by the traditional mastery goal theorists. The *medium mastery-differentiated* students (profile 2; 31%) were also mastery-oriented like the profile 1 students, however, they had higher levels of both performance goals. The *high non-differentiated* students (profile 3; 11%) expressed high levels of mastery goals but also high levels of performance-approach and performance-avoidance goals. In contrast, *the revised goals perspective* students (profile 4; 11%) were characterized by high mastery and performance-approach goals but relatively low performance-avoidance goals. The *medium non-differentiated* students (profile 5; 14%) were characterized by relatively higher levels of mastery and performance-avoidance goals relative to performance-approach goals. The *low mastery-differentiated* students (profile 6; 8%) expressed low achievement goals for mathematics overall but relatively higher mastery goals.

Main Effects of Classroom Goal Structure

To answer the second research question, a series of SEMs were conducted to examine the "main effect" of classroom goal structure (both individual student perceptions and classroom aggregate measures) on the various student outcomes across the entire sample.

Student perceptions (L1) models. Table 3.5 presents the results from a series of 11 SEMs with individual student perceptions (L1) of their math classrooms' mastery and performance-approach goal structure assessed in the Fall predicting changes in students' motivational beliefs (self-efficacy, interest), affect (positive and negative), behavior (help seeking), and achievement (math course grade and standardized achievement) assessed in the

Spring. Students' prior mathematics achievement and the baseline (Fall) measures of the outcomes were controlled for in the models in order to investigate how classroom goal structure is associated with over-the-year change. As expected, prior measures of the outcomes were predictive of Spring measures of the outcomes. Holding all else constant, prior standardized mathematics achievement was associated with positive over-the-year change in self-efficacy beliefs ($\beta = 0.16$, $p < .001$), interest in mathematics ($\beta = 0.08$, $p < .01$), and peer help seeking ($\beta = 0.05$, $p < .05$), and declines in avoidant help seeking ($\beta = -0.05$, $p < .01$) and negative affect ($\beta = -0.04$, $p < .05$). Holding all else constant, individual student perceptions of classroom mastery goal structure was associated with increases in adaptive outcomes [self-efficacy ($\beta = 0.07$, $p < .001$), positive affect ($\beta = 0.04$, $p < .05$), instrumental help seeking ($\beta = 0.23$, $p < .001$), seeking help from peers ($\beta = 0.14$, $p < .001$) and the teacher ($\beta = 0.07$, $p < .01$), and math course grade ($\beta = 0.12$, $p < .001$)] and decreases in maladaptive outcomes such as negative affect ($\beta = -0.05$, $p < .05$) and avoidant help seeking ($\beta = -0.06$, $p < .01$). In contrast, individual perceptions of classroom performance-approach goal structure were associated with positive over-the-year changes in maladaptive help-seeking tendencies—avoidant ($\beta = 0.08$, $p < .001$) and expedient help seeking ($\beta = 0.14$, $p < .001$).

{INSERT TABLE 3.5 HERE}

Classroom aggregate (L2) models. Table 3.6 presents the results from the same series of SEMs as before but with classroom aggregate measures (L2) or shared student perceptions of their math classroom's mastery and performance-approach goal structure assessed in the Fall predicting students' outcomes assessed in the Spring.[8] As expected, prior measures of the

[8] I conducted the main effects models using both clustered standard errors and multilevel modeling. However, multi-level multigroup SEM is not possible in *Mplus*, therefore I only present results from the models using clustered standard errors for all L2 analyses. For the main

outcomes were predictive of Spring measures of the outcomes. Holding all else constant, prior mathematics achievement was associated with a decline in avoidant help seeking (β = -0.05, $p < .01$) and increases in self-efficacy beliefs (β = 0.13, $p < .001$), peer help seeking (β = 0.05, $p < .05$), and interest in mathematics (β = 0.07, $p < .001$). Holding all else constant, classroom collectively perceived as mastery oriented were associated with over-the-year increases in adaptive outcomes [positive affect (β = 0.06, $p < .05$), instrumental help seeking (β = 0.08, $p < .001$), and seeking help from peers (β = 0.05, $p < .05$) and the teacher (β = 0.05, $p < .05$)] and decreases in negative affect (β = -0.06, $p < .05$). In contrast, classrooms collectively rated as performance-approach oriented were associated with declines in adaptive outcomes [self-efficacy (β = -0.11, $p < .05$), instrumental help seeking (β = -0.07, $p < .001$), and asking peers (β = -0.04, $p < .05$) and the teacher for help (β = -0.15, $p < .05$)] as well as positive over-the-year changes in the tendency to engage in avoidant help seeking (β = 0.05, $p < .01$).

{INSERT TABLE 3.6 HERE}

Does Classroom Goal Structure Have the Same Effect for the Various Student Goal Profiles?

A series of multigroup SEMs tested whether the relations between classroom goal structure (both individual student perceptions and classroom aggregate measures) and the various outcomes found in the main effects models held true for the various student goal profiles. Specifically, the same SEM depicted in Figure 3.2 was simultaneously conducted separately for two contrasted latent personal goal profile groups. In step 1 for the multigroup SEM (Figure 3.4a), all structural parameters were allowed to be freely estimated across the two latent profile

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effects analyses, both types of models produced the same pattern of results with the exception of the L2 mastery goal structure no longer being a statistically significant predictor of negative affect in the multilevel model.

groups. For example, the regression coefficient or estimated "effect" of classroom mastery goal structure was allowed to differ between latent profile groups, such as the profile of students who are highly mastery oriented (mastery goals perspective) versus the profile of students who are both highly mastery and performance-approach oriented (revised goals perspective). In step 2 (Figure 3.4b), one of the regression paths (e.g., for mastery goal structure) was constrained to be equal across the two profile groups while all the other structural parameters were still allowed to be freely estimated across the groups. This reflects the assumption that mastery goal structure has the same "effect" across the groups, regardless of the students' motivational profile. The last step compared the change in model fit between steps 1 and 2. If the change in model fit is not statistically significant, this suggests that forcing the estimated effect of mastery goal structure to be the same across the sample does not worsen the model fit. That is, the effect of classroom mastery goal structure is the same regardless of students' motivational profile. In contrast, if the change in model fit between steps 1 and 2 is statistically significant, this indicates that constraining the regression path to be the same across the groups worsens the model fit. This suggests that the estimated effect of classroom goal structure is different for the different achievement goal profile groups. The same three steps were conducted separately for constraining mastery goal structure's and performance-approach goal structure's regression coefficients.

{INSERT FIGURE 3.4 HERE}

First, I attempted to test a multigroup SEM allowing all structural parameters to be freely estimated across the six latent student goal profile groups. This omnibus test ran into model identification issues as this model was asking for more parameters to be estimated than the data could handle (i.e., unique structural parameters estimated for each of the six groups).

Next, I tested planned contrasts comparing specific student goal profile groups that theory and extant research suggested would fare differently under specific classroom goal structure conditions. Specifically, I tested four planned contrasts in the multigroup SEMs: (1) the *mastery goals perspective* vs. *revised goals perspective* (profiles 1 vs. 4); (2) the *mastery goals perspective* vs. the *low mastery-differentiated* (profiles 1 vs. 6); (3) *high non-differentiated* vs. *revised goals perspective* (profiles 3 vs. 4); and (4) *medium mastery-differentiated* vs. *medium non-differentiated* (profiles 2 vs. 5). Below, I discuss why I chose to compare these four specific contrasts.

The *mastery goals perspective* and *revised goals perspective* (profiles 1 vs. 4) groups are similar on their reported levels of personal mastery goals and performance-avoidance goals but differ on their levels of personal performance-approach goals, with the *revised goal perspective* students reporting higher performance-approach goals. The *mastery goals perspective* and the *low mastery-differentiated* (profiles 1 vs. 6) groups both have low performance-approach and –avoidance orientation. However, profile 6 has a maladaptive motivational profile with low goal orientation overall, whereas profile 1 reflects the traditional mastery perspective, which should be very adaptive. The *high non-differentiated* and *revised goals perspective* (profiles 3 vs. 4) groups have similar levels of personal mastery and performance-approach goals for mathematics, however, Profile 3 students (*high non-differentiated*) reported higher levels of performance-avoidance goals than Profile 4 students (*revised goals perspective*). Lastly, *medium mastery-differentiated* and *medium non-differentiated* (profiles 2 vs. 5) share similar high levels of personal mastery goals and lower performance-approach goals for mathematics. However, the *medium non-differentiated* students (profile 5) reported significantly higher performance-avoidance goals than profile 2 students, almost at the same level of mastery goals.

The multigroup SEMs comparing these two groups for each contrast tested whether mastery and performance-approach goal structure may be especially beneficial or detrimental for one profile group than the other profile group. For example, perhaps the *low mastery-differentiated* students may have more room to grow and benefit in a mastery-oriented classroom than the *very mastery goals perspective* students. Or could the negative effects of performance-approach goal structure found in the main effects model be more harmful for one profile group than the other?

For the first step of multigroup SEM, I tested the null models (all structural parameters are freely estimated across the two groups but the regression coefficient from classroom mastery goal structure to the outcome is constrained to be equal for both profiles) to the alternative model (all structural coefficients are freely estimated across the two profile groups). Typically a chi-square difference test is used to the difference in model fit between nested models. However, because the MLR estimator was used to account for the nested nature of the data, a chi-square difference test based on log-likelihood values and scaling correction factors obtained from the MLR estimator was used instead (Asparouhov & Muthén, 2013).[9] The Bonferroni correction was used for the multiple, planned, pairwise, orthogonal contrasts. For 11 contrasts, this yielded a conservative $p < .0045$ criterion for significance at the individual level (Maxwell & Delaney, 2004). For each of the four contrasts and across the 11 outcomes of interest, constraining the regression path from mastery goal structure (L1 and L2 measures) to be the same across the groups did not statistically worsen the model fit, suggesting that the estimated effect of perceived

[9] When using the MLR estimator, the Satorra-Bentler (SB) scaled chi-square difference test is also appropriate for comparing nested models. However, the alternative models where all parameters were allowed to be freely estimated were just identified, resulting in a chi-square value of 0. Therefore, useful chi-square values could not be obtained to calculate the SB scaled chi-square difference test. Nonetheless, both the SB and loglikelihood difference test lead to the same result (Asparouhov & Muthén, 2013).

classroom mastery goal structure is the same for these profile groups (see chi-square difference test based on log-likelihood values tables in Appendix B).

Another set of multigroup SEMs tested whether the estimated effect of classroom performance-approach goal structure differed between the profiles. For example, does the estimated effect of performance-approach goal structure differ between students who represent the mastery perspective versus the revised goal perspective? Across the 11 outcomes of interest, constraining the regression path from performance-approach goal structure (L1 and L2) to be the same across the profiles did not statistically worsen the model fit after using the corrected *p*-value (see tables in Appendix B). However, one exception was the multigroup SEM comparing Profiles 1 and 4 with L2 performance-approach goal structure predicting to end-of-year math course grades. The statistically significant worsened model fit suggested that L2 performance-approach goal structure's regression coefficient should not be constrained across the two profile groups (Table 3.7). Figure 3.5 provides the unstandardized regression coefficients and covariances separately for profile 1 (Figure 3.5a) and profile 4 (Figure 3.5b). For *mastery goals perspective* students (profile 1) who are characterized by high personal mastery goals and low performance goals for math, being in classrooms collectively rated as being performance-approach oriented did not have an association with end-of-the-year math grades—similar to the null association between L2 classroom performance-approach and math grades found in the main effects analyses (Table 3.6). In contrast, classrooms collectively rated as being performance-approach oriented were positively associated with math course grades for the *revised goals perspective* students (b = 0.76, SE = 0.36, $p < .05$), who—similar to the *mastery goals perspective students*—endorse high personal mastery goals but also high performance-approach goals for math.

{INSERT TABLE 3.7 HERE}

{INSERT FIGURE 3.5 HERE}

In summary, the LPA results from Study 1 indicate that students are differently motivated. Using sample means would have lost these individual differences in the various constellations of achievement goals as they exist within individuals. SEM results examining the main effects of classroom goal structure revealed that both individual and shared perceptions of classroom mastery goal structure was associated with positive over-the-year change in adaptive student outcomes and declines in maladaptive outcomes. Conversely, both individual and shared perceptions of classroom performance-approach goal structure were associated with increases in maladaptive student outcomes and decreases in adaptive outcomes. Taken together with the one finding as the exception, the results from planned contrasts between specific goal profile groups using multigroup SEM revealed that the estimated effect of mastery and performance-approach goal structure was similar across this sample of students. For the most part, mastery goal structure was similarly beneficial and performance-approach goal structure was similarly detrimental within this sample of students. Although classrooms collectively perceived as emphasizing performance-approach goals were not associated with math course grades, for students who endorsed both mastery and performance-approach goals for math, being in a performance-oriented classroom was associated with higher grades. With the exception of this one finding supporting the matching hypothesis, the majority of the results from the planned contrasts suggest that the alignment or misalignment between classroom and students' goals does not matter for the 11 outcomes of interest.

Study 3: Replication and Longitudinal Extension

Due to need for more replication studies (Koole & Lakens, 2012), Study 3 replicates the analyses in Study 2 to investigate whether the same pattern of results hold with a separate sample of students surveyed in a different year (2004-2005) of the larger study from which this data comes from. For instance, it is possible that different personal goal profiles may emerge in a different sample of students, allowing further examination of the different ways classroom and students' personal goals can come together. Furthermore, Study 3 is concerned with variations in longitudinal trends as a function of multiple personal and classroom goals and examines the longitudinal consequences of the (mis)match between students' personal goals and the classroom goals by examining outcomes both at the end of the year (Spring 2005) and also a year later (Spring 2006). In previous studies, researchers have examined the predictive effects of multiple personal goals in students cross-sectionally and longitudinally to examine the effects of various profiles of goals (e.g., Conley, 2012; Pastor et al., 2007; Pintrich, 2000; Tuominen-Soini et al., 2008). In this study, I hope to provide insight into the longitudinal consequences of various profiles of personal goals as they interface with their math classroom's goals. Specifically, this study tests the same three research questions tested in Study 2:

1. What are the different patterns of students' personal achievement goals (mastery, performance-approach, and performance-avoidance)?
2. Are math classrooms' goal structure (mastery and performance-approach) related to students' motivation (self-efficacy, interest, affect, achievement goals), behavior, (help seeking), and learning (end-of-year math course grade and standardized achievement) in the short-term and long-term?

3. Do classroom goal structures have differential short- and long-term effects depending on students' personal achievement goal profiles?

Methods

Participants

Study 3's participants are 1,287 seventh and eighth grade students (711 seventh grade students and 576 eighth grade students) from 103 mathematics classrooms in six Southern California middle schools in 2004-2005. The average classroom size consisted of 16 students with a range of class size from 6 to 28 (SD = 4.87). These students were observed across both years as part of the larger study from which this data comes from. In Study 3, I examine students from the 2004-2005 school year and their longitudinal outcomes measured at Spring 2006. Surveys were administered in the Fall and Spring for both years. Students' scores from the CST taken in the Spring 2004 (baseline), 2005, and 2006 were obtained. Students must have had valid survey responses from Fall 2004, Spring 2005, and Spring 2006 and achievement data to be included in the study.

Measures

The same measures from Study 2 were used in Study 3. Descriptive statistics for this sample and the psychometric properties of the scales are provided in Table 3.8. Correlations between measures of classroom goal structure, students' personal goals, and short-term outcomes and long-term outcomes are provided in Tables 3.9 and 3.10, respectively.

{INSERT TABLES 3.8, 3.9, 3.10 HERE}

Analysis Plan

Study 3 is a replication of study 2 and thus shares the same analysis plan: 1) latent profile analysis on students' personal achievement goals, 2) SEMs estimating the main effect of L1 and

L2 classroom goal structure; and 3) multigroup SEMs testing whether the associations between L1 and L2 classroom goal structure and the 11 outcomes vary between specific student profile groups. Study 3 also examines the long-term effects of classroom goal structure and the matching hypothesis. Therefore, the additional main effect analyses and multigroup SEMs test how classroom mastery and performance-approach goal structure assessed in the Fall relate to the various outcomes of interest assessed in Spring 2005 and Spring 2006. These models controlled for students' prior standardized mathematics achievement (Spring 2004) as well as Fall 2005 measures of the outcomes in order to examine how classroom goal structure is associated with short-term (Spring 2005) and long-term (Spring 2006) changes.

Again, the nested structure of the data with students nested within classrooms was taken into account using TYPE = MIXTURE COMPLEX in *Mplus 6.12*. All analyses were conducted using a robust maximum likelihood estimator (MLR), which provides estimates of standard errors and chi-square statistic that are robust to nonnormality and nonindependence of observations when accounted for the nested nature of data.

Results

Latent Student Achievement Goal Profiles

Using theory, a suite of model fit indices, and model entropy, the results from a series of LPA suggested that a 6-class solution fit the data best (Table 3.11). The average personal achievement goal scale scores for the six profiles are provided in Table 3.12 and Figure 3.6 provides a visual depiction of the same information. The six groups were labeled as: 1) medium mastery-differentiated, 2) medium non-differentiated, 3) mastery goals perspective, 4) low non-differentiated, 5) revised goals perspective, and 6) high non-differentiated.

{INSERT TABLES 3.11 & 3.12 HERE}

{INSERT FIGURE 3.6 HERE}

As Table 3.12 and Figure 3.6 illustrate, the *medium mastery-differentiated* (profile 1; 20% of the sample) had low personal performance-approach and –avoidance goals for math and relatively higher mastery goals. The *medium non-differentiated* students (profile 2; 16%) expressed that they were equally oriented on all goal three dimensions (approximately a rating of 3 out of the 5-point scale). The *mastery goals perspective* students (profile 3; 28%) expressed high levels of mastery goals and low levels of performance goals, representing the most adaptive motivational profile as hypothesized by the traditional goal theorists. In contrast, the *low non-differentiated* students (profile 4; 3%) expressed low achievement goals for mathematics overall. The *revised goals perspective* students (profile 5; 19%) were characterized by high mastery and performance-approach goals but low performance-avoidance goals. The *high non-differentiated* students (profile 6; 14%) expressed high levels of mastery goals but also high levels of performance-approach and performance-avoidance goals.

Main Effects of Classroom Goal Structure

Next, a series of SEMs were conducted to examine the association between classroom goal structure (both individual student perceptions and classroom aggregate measures) and the various student outcomes assessed at the end of the school year (Spring 2005) and a year later (Spring 2006).

Student perceptions (L1) models. Table 3.13 presents the results from a series of 11 SEMs with individual student perceptions (L1) of their math classroom's mastery and performance-approach goal structure assessed in the Fall predicting students' motivational beliefs (self-efficacy, interest), affect (positive and negative), behavior (help seeking), and achievement (math course grade and standardized achievement) reported at the end of the year.

Students' prior standardized mathematics achievement and the baseline (Fall) measures of the outcomes were controlled for in the models to investigate how classroom goal structure is associated with over-the-year change. As expected, prior measures of the outcomes were predictive of Spring measures of the outcomes. Holding all else constant, prior mathematics achievement was associated with positive over-the-year change in self-efficacy beliefs ($\beta = 0.17$, $p < .001$) and interest in mathematics ($\beta = 0.06$, $p < .05$). Holding all else constant, individual student perceptions of classroom mastery goal structure was associated with increases in adaptive outcomes [self-efficacy ($\beta = 0.06$, $p < .05$), instrumental help seeking ($\beta = 0.23$, $p < .001$), seeking help from peers ($\beta = 0.17$, $p < .001$) and the teacher ($\beta = 0.14$, $p < .001$), and math course grade ($\beta = 0.13$, $p < .001$)] and decreases in maladaptive outcomes [expedient ($\beta = -0.08$, $p < .01$) and avoidant help seeking ($\beta = -0.11$, $p < .001$)]. In contrast, individual perceptions of classroom performance-approach goal structure were associated with positive over-the-year changes in maladaptive help-seeking tendencies [avoidant ($\beta = 0.09$, $p < .01$) and expedient help seeking ($\beta = 0.10$, $p < .001$)] and lower math course grades ($\beta = -0.05$, $p < .05$).

{INSERT TABLE 3.13 HERE}

Table 3.14 presents results from a series of SEMs examining the association between L1 classroom goal structure (Fall 2004) and the same outcomes but assessed a year after (Spring 2006). Prior measures of the outcomes assessed in Fall 2004 were still predictive of the same outcomes almost two years later. Holding all else constant, prior standardized mathematics achievement was associated with declines in avoidant help seeking ($\beta = -0.08$, $p < .05$) and positive changes in self-efficacy beliefs ($\beta = 0.15$, $p < .001$), interest in mathematics ($\beta = 0.05$, $p < .05$), and instrumental ($\beta = 0.08$, $p < .01$) and peer help seeking ($\beta = 0.10$, $p < .001$) two years later. Holding all else constant, individual student perceptions of classroom mastery goal structure was associated with increases in adaptive outcomes [instrumental help seeking (β = 0.19, $p < .001$), seeking help from peers (β = 0.14, $p < .001$), seeking help from their new math teacher (β = 0.09, $p < .001$), and end-of-year grade in the new math course (β = 0.11, $p < .01$)] and decreases in maladaptive outcomes [expedient (β = -0.10, $p < .001$) and avoidant help seeking (β = -0.06, $p < .05$)] and interest in math (β = -0.07, $p < .05$) assessed a year after taking that math course. In contrast, individual perceptions of classroom performance-approach goal structure were associated with positive changes maladaptive outcomes assessed almost two years later [negative affect (β = 0.07, $p < .01$), avoidant help seeking (β = 0.07, $p < .05$), and expedient help seeking (β = 0.10, $p < .001$)] but also an increase in standardized mathematics achievement (β = 0.05, $p < .05$).

{INSERT TABLE 3.14 HERE}

Classroom aggregate (L2) models. Tables 3.15 and 3.16 presents results from the same series of SEMs as before but with classroom aggregate measures (L2) or shared student perceptions of their math classroom's mastery and performance-approach goal structure assessed in Fall 2005. For models predicting over-the-year changes in outcomes (Table 15), prior measures of the outcomes were predictive of Spring measures of the outcomes. Holding all else constant, classroom collectively perceived as mastery oriented were associated with increases in adaptive outcomes [end-of-year math course grade (β = 0.12, $p < .05$), instrumental help seeking (β = 0.10, $p < .05$), and seeking help from peers (β = 0.09, $p < .05$)] and decreases in negative affect (β = -0.09, $p < .05$) and standardized math achievement (β = -0.10, $p < .01$).[10] Classrooms

[10] The outcome, students' 2006 math CST score, was standardized within math test type because 8th grade students can take different test types (8th grade general, Algebra 1, or Geometry), whereas all 7th grade students take the 7th grade general test. Upon further investigation for why L2 mastery goal structure was associated with declines in standardized achievement, 8th graders who took the Algebra 1 test on average dropped 12 points on their math CST scores from the

collectively rated as performance-approach oriented were not associated with over-the-year changes in any of the 11 outcomes. As for examining changes in these outcomes almost two years later (Table 3.16), classrooms that were collectively judged as mastery-oriented were associated with increases in instrumental help seeking ($\beta = 0.10$, $p < .01$) and peer help seeking ($\beta = 0.08$, $p < .05$); whereas, classrooms collectively judged as performance-approach oriented were associated with declines in interest in math ($\beta = -0.05$, $p < .05$).

{INSERT TABLES 3.15 & 3.16 HERE}

Does Classroom Goal Structure Have the Same Effect for the Various Student Goal Profiles?

A series of multigroup SEMs tested whether the relations between classroom goal structure (both individual student perceptions and classroom aggregate measures) and the various outcomes found in the main effects models held true for the various student goal profiles. Similar to Study 2, I tested planned contrasts comparing specific student goal profile groups that theory and extant research suggested would fare differently under specific classroom goal structure conditions. Specifically, I tested three planned contrasts in the multigroup SEMs: (1) the *mastery goals perspective* vs. *revised goal perspective* (profiles 3 vs. 5); (2) *revised goals perspective* vs. *high non-differentiated* (profiles 5 vs. 6); and (3) *medium mastery-differentiated* vs. *mastery goals perspective* (profiles 1 vs. 3). Below, I discuss why I chose to compare these three specific contrasts.

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prior year whereas all other 7th and 8th grade students performed similarly or better than the year before. During the time of data collection, the school districts in the larger study were midway in implementing a policy where all 8th grade students must take the Algebra test. It is possible that underprepared students who, under the Algebra-for-all policy, had to take the Algebra test were bringing down the group-mean for the 2006 CST math scores (for other research who have found declines in math achievement associated with Algebra-for-all policies, see Clotfelter, Ladd, & Vidgor, 2012; Williams et al., 2011).

The *mastery goals perspective* and *revised goal perspective* groups (profiles 3 vs. 5) are similar on their reported levels of personal mastery goals, differ a little on their reported performance-avoidance goals, but differ more on their levels of personal performance-approach goals. The *revised goals perspective* and *high non-differentiated* groups (profiles 5 vs. 6) are similar on their expressed levels of personal mastery and performance-approach goals for math. However, the *high non-differentiated* report similar levels of performance-approach and –avoidance goals whereas the *revised goals perspective* students' performance-avoidance goals are much lower than their performance-approach goals. The *medium mastery-differentiated* and *mastery goals perspective* groups (profiles 1 vs. 3) share similar low levels of performance-approach and performance-avoidance goals for mathematics. Both profiles report higher levels of personal mastery goals relative to the performance goals, but the *mastery goals perspective* students' mastery goals are higher than the *medium mastery-differentiated* students' personal mastery goals.

The Bonferroni correction was used for the multiple, planned, pairwise, orthogonal contrasts. For 11 contrasts, this yielded a conservative $p < .0045$ criterion for significance at the individual level (Maxwell & Delaney, 2004). Across the 11 outcomes of interest assessed at the end of the school year (Spring 2005) and a year after (Spring 2006) constraining the regression path from L1 and L2 mastery goal structure to be the same across the profiles did not statistically worsen the model fit (see tables in Appendix C). Altogether, the null results from the log-likelihood difference test with L1 and L2 measures of mastery goal structure suggest that the estimated effect of perceived mastery goal structure on both short- and long-term outcomes is the same for the contrasted student profile groups.

Another set of multigroup SEMs tested whether the estimated effect of classroom performance-approach goal structure differed between the contrasted groups. For example, does the estimated effect of performance-approach goal structure differ between students who represent the mastery goals perspective versus the revised goals perspective? Across the 11 outcomes of interest assessed at the end of the school year, constraining the regression path from L1 performance-approach goal structure to be the same across the contrasted profile groups did not statistically worsen the model fit after using the corrected *p*-value (see Appendix C). When using classroom aggregate measure of performance-approach goal structure to predict to the 11 outcomes assessed at the end of the year (Spring 2005) and a year later (Spring 2006), constraining the regression path from L2 performance-approach goal structure to be the same across the contrasted profiles did not statistically worsen the model fit after using the corrected *p*-value (see Appendix C), with the exception of the contrast between profiles 3 and 5 and the model predicting to over-the-year changes in positive affect (Table 3.17). The statistically significant worsened model fit suggests that L2 performance-approach goal structure's regression coefficient should not be constrained across the two profile groups. Figure 3.7 provides the unstandardized regression coefficients and covariances separately for profile 3 (Figure 3.7a) and profile 5 (Figure 3.7b). Classrooms collectively rated as being performance-approach oriented was not associated with over-the-year changes for the *mastery goals perspective* students (profile 3)—similar to the null association between L2 classroom performance-approach and positive affect found in the main effects analyses (Table 3.15). In contrast, classrooms collectively rated as being performance-approach oriented was associated with declines in positive affect for the *revised goals perspective* students (profile 5) who expressed both high personal mastery goals and performance-approach goals ($b = -0.45$, $SE = 0.19$, $p < .05$).

{INSERT TABLE 3.17 HERE}

{INSERT FIGURE 3.7 HERE}

Discussion

Identifying and understanding features of effective classroom climates that foster student motivation, strategy use, and learning is the crux of educational research. In studies 2 and 3 of my dissertation, I examined whether the math classrooms' goal structure, as perceived by students, "work differently" for various students. The few extant studies demonstrate that students' experiences of matches and mismatches between their personal and classroom goals have consequences (Barron & Harackiewicz, 2003; Lau & Nie, 2008; Murayama & Elliot, 2009; Wolters, 2004). It is critical to investigate whether these experiences of matches and mismatches over time lead to short-term and long-term changes on a broad range of important outcomes. The current two studies addressed three research questions. First, what are the patterns of students' personal achievement goals? Second, how are math classrooms' goal structure related to students' motivation (self-efficacy, interest, affect), behavior, (help seeking), and learning (math course grade and standardized achievement)? Third, do classroom goal structures have differential effects depending on students' personal achievement goal profiles? To investigate these issues, studies 2 and 3 employed pattern-centered approaches to examine the naturally occurring patterns of students' personal achievement goals that emerge in this large sample of middle school students. Next, these two studies employed multigroup SEM to test whether the associations between perceived classroom goal structure and various critical outcomes differ by students' motivational profiles. Each of the findings and their contributions are discussed below.

Both studies 1 and 2 found six similar profiles of student motivational goal profiles and demonstrated important differences between these students in terms of patterns of mastery, performance-approach, and performance-avoidance goals. For example, some profiles were highly differentiated between the three goals (e.g., high mastery and low performance goals, or higher mastery and performance-approach but low performance-avoidance) whereas some profile groups reported undifferentiated levels between the three goal orientations (e.g., low on all goals). Similar profiles of personal achievement goals have also been found with European secondary school students, though a performance-avoidant group was not found within the current sample (Tuominen-Soini et al., 2008). This approach of looking at the relative emphasis of different goal orientations provides a promising alternative to investigate the issue of multiple goals as they reside within individuals. These individual differences in student motivation would have been lost had latent profile analysis was not utilized. These two current studies as well as others (Conley, 2012; Pastor et al., 2007; Tuominen-Soini et al., 2008) illustrate the need for a multidimensional perception of student motivation and that these distinctions in patterns of motivation, rather than mean-level differences, are important to maintain.

Overall, the findings from the two studies overwhelmingly suggest that both individual perceptions and shared perceptions of classroom mastery goal structure were related to adaptive changes in help-seeking tendencies, self-efficacy beliefs, and affect, and that some of these benefits were still present a year later. In contrast, the results also overwhelmingly suggest that both individual perceptions and shared perceptions of classroom performance-approach goal structure were associated with increases in maladaptive outcomes such as negative affect, avoidant help seeking, and expedient help seeking. Altogether, the findings suggest that the perceived classrooms' goals matter and that teachers should be cognizant of how their instructional practices and classroom policies may inform students' perceptions of the goals of the classroom. For example, research employing qualitative analyses of classroom discourse suggest that high mastery classrooms are characterized by teacher emphasis on effort, encouragement of social interaction, and instructional practices such as providing students opportunities to demonstrate new abilities, providing motivational support for learning, and helping students understand complex topics (Patrick et al., 2001; Turner et al., 2002). In contrast, studies have found that teachers of highly performance-oriented classrooms emphasize formal assessments, grades, and students' relative performance (e.g., Patrick et al., 2001).

The two current studies included a broad range of different types of learning-related outcomes to investigate the short-term and long-term effects of the alignment or misalignment between students' and classrooms' goals. The overall pattern of null findings testing the matching hypothesis suggest that within this sample of middle school students mastery goal structure was equally beneficial for everyone, and that performance-approach goal structure, at best, had no effect and, at worst, was detrimental to students' help-seeking tendencies and self-efficacy beliefs. With two competing findings as the exception, there was very little evidence supporting the matching hypothesis. In study 2's sample, being in a math classroom collectively rated as being performance-approach oriented was not linked with end-of-the-year math grades. However, compared to students who solely focused on mastery goals, students who personally endorsed both mastery and performance-approach goals fared well in these types of classrooms, suggesting that a match between classroom and students' performance-approach goals is beneficial in terms of math course grades. This finding supports the revised goals perspective, which argues that performance-approach goals are not always maladaptive and that they can be beneficial when mastery goals are also high. However, competing results were found with study's 3 sample of 7th and 8th grade students. Contrary to what the revised goals theory would hypothesize, students representative of the revised goals perspective (high mastery and performance-approach goals but low performance-avoidance orientation) in classrooms collectively rated as emphasizing performance-approach goal structure reported declines in positive affect over the school year. In contrast, students representative of the mastery goals perspective (high mastery goals and low performance orientation) on average did not experience significant declines in positive affect. It appears that the potential negative effects of students' personal performance-approach goals were amplified in a performance-oriented learning environment, supporting the vulnerability-stress hypothesis (Ingram & Luxton, 2005). These findings suggest that performance-approach goals can be beneficial for achievement outcomes, but they come with a cost. In addition, though these two finding indicate that the effect of classroom goals sometimes differ for differently motivated students, the overall pattern of findings from the main effects analyses and the null multigroup analyses suggest that perceptions of classroom performance-approach goal are detrimental.

These two studies contribute to achievement goal theory research as well as research more broadly by demonstrating a method to investigate person-environment fit issues while preserving the various complex patterns of goal orientations within individuals. Although there were mainly null findings for the matching hypothesis, this study illustrates one way to capture person-environment fit in a complicated, messy world. Another study that also employed this method is a study by Bowers and colleagues (2014), which examined parenting profiles and tested whether profile membership moderated the associations between non-parental adult relationships and positive youth development. Clearly, this approach has much potential for testing questions about person-context interactions or cross-context interactions (e.g., classroom achievement goals and family achievement goals) to capture the multiple factors that come together to shape development.

In terms of limitations, both studies' samples consisted of mainly Latino and Asian (primarily Mexican and Vietnamese) students from working-class backgrounds. On one hand, the sample is unique and more research is needed to understand the motivational profiles of this diverse group of students. The vast majority of motivation research is conducted on middle class White students (Urdan & Giancarlo, 2001). On the other hand, these findings may not be generalizable to other groups. Given the increasing presence of Latino immigrant families in the U.S. public systems (Pew Hispanic Center, 2009), future research is needed to understand whether goal orientations relate the same way with different ethnic groups. In addition, the two current studies examined whether the alignment or misalignment between classroom and students' personal goals matter with a sample of middle school students. During high school and college, the pressure to perform is made more salient by normed grading practices, the growing importance of standardized tests, and the college and graduate school application process. It is plausible that with these age groups, the student profiles as well the classrooms look different. Therefore, the generalizability of these findings may be limited with regard to age (or school type) as well.

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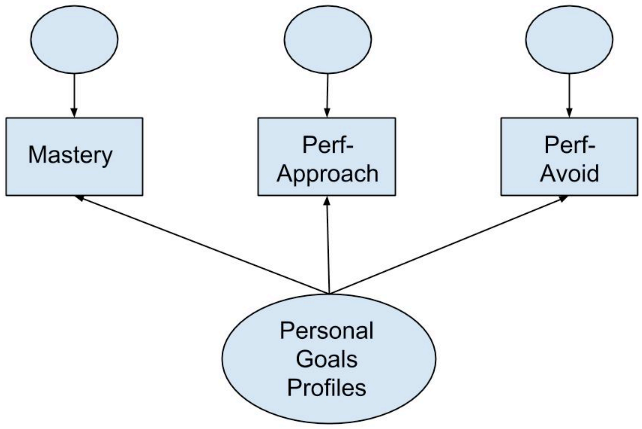


Figure 3.1. This latent profile analysis (LPA) measurement model was used to capture profiles of personal goal orientation for mathematics. Each individual's scale score for personal mastery, performance-approach, and performance-avoidance goal orientation was used to categorize him/her into a profile group, which can be visually represented by profile plots.

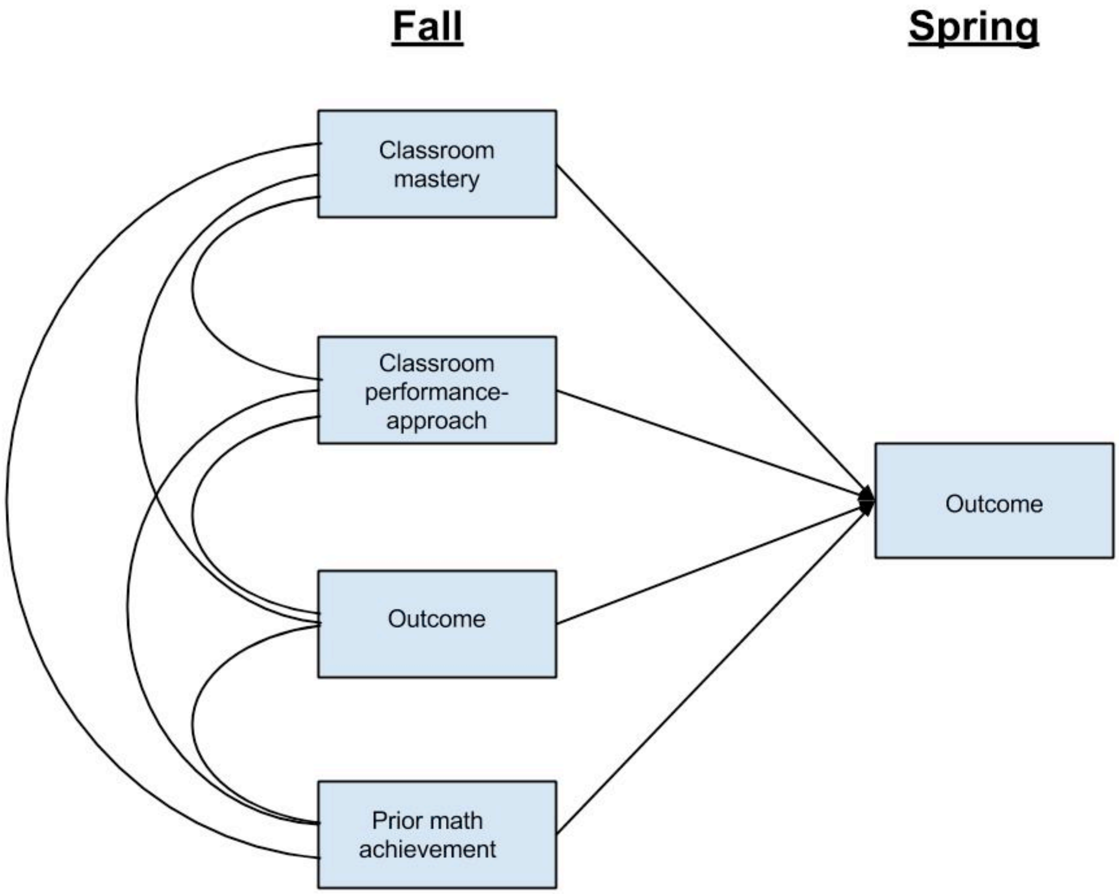


Figure 3.2. SEM examining the main effect of classroom goal structure on the 11 outcomes. The models control for baseline (Fall) measures of the outcome in order to examine how classroom goal structure is related to over-the-year changes in the outcomes. The model also controls for students' prior standardized math achievement (assessed in the Spring from the prior academic year). Parallel analyses were conducted with L1 and L2 measures of classroom goal structure.

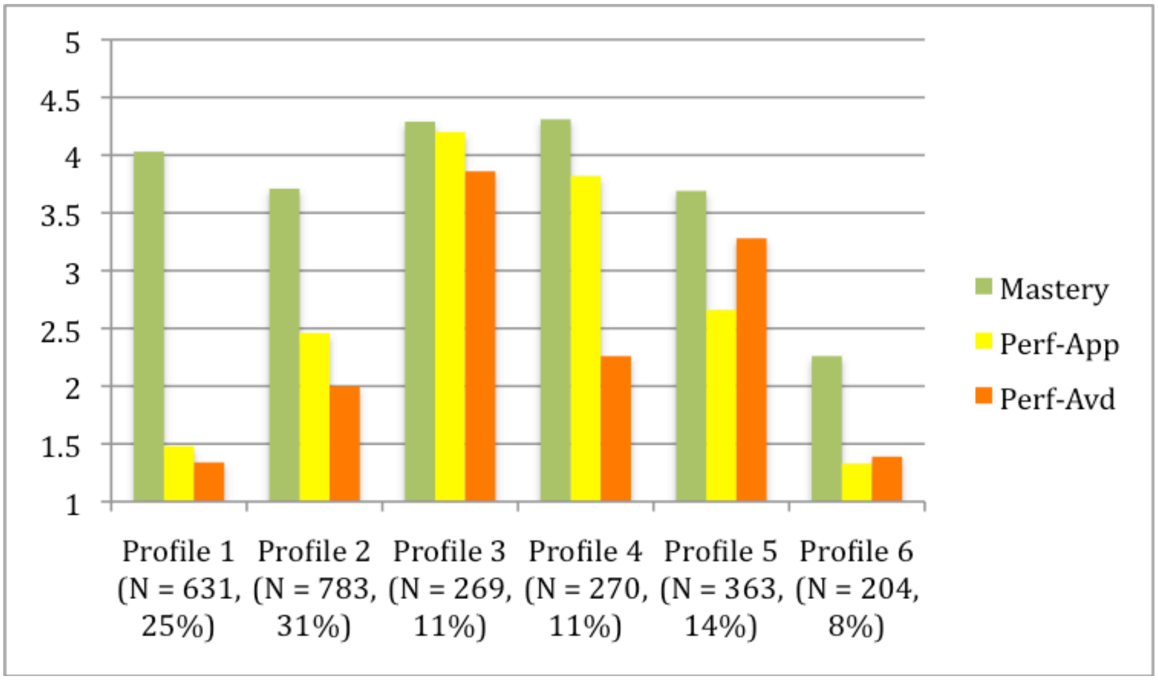
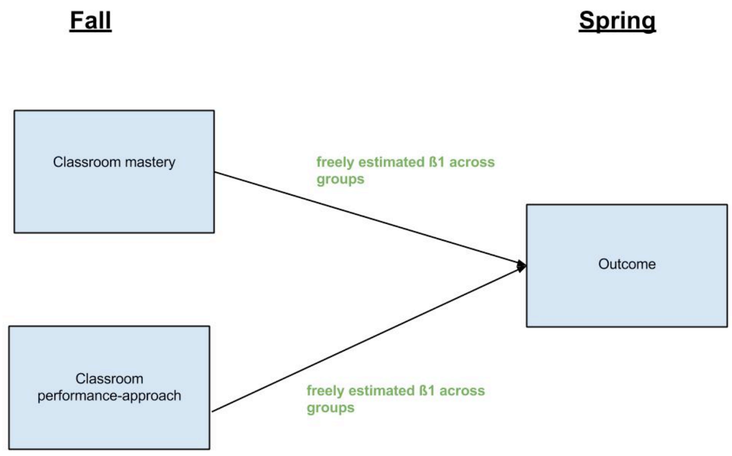
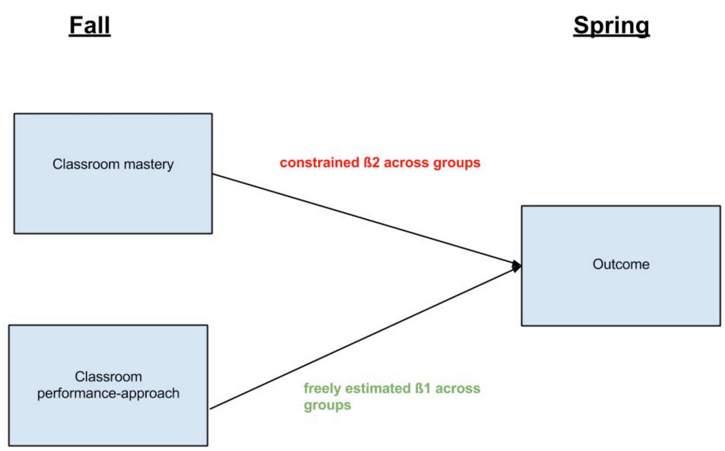


Figure 3.3. Latent profile groups of students based on their personal achievement goals for mathematics for Study 2's sample.

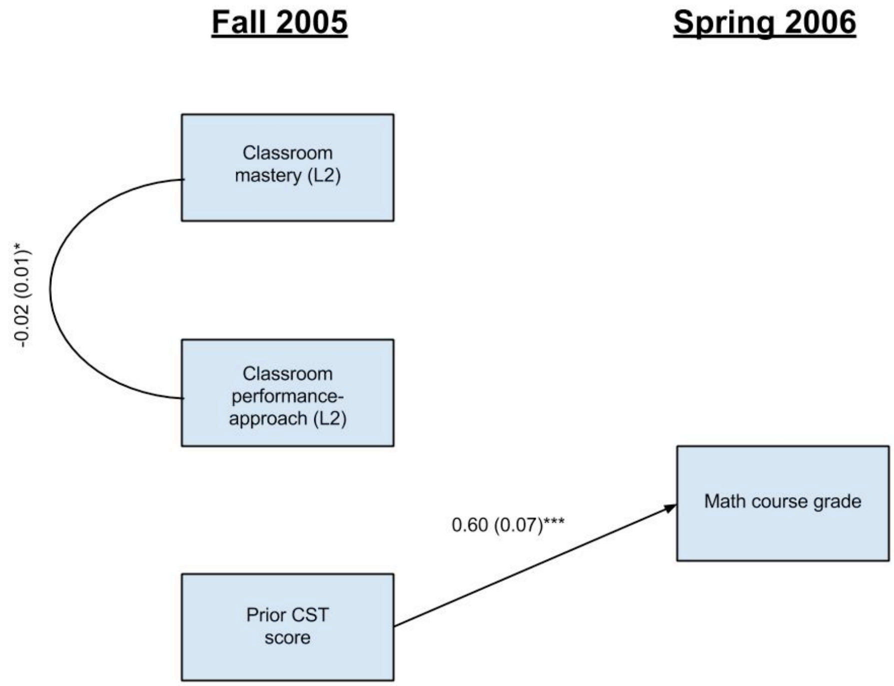


(a)

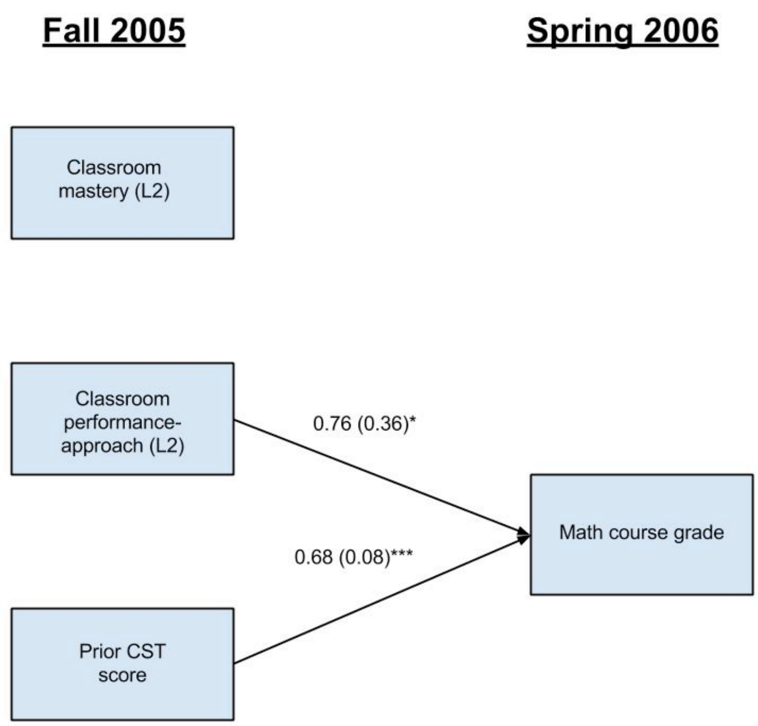


(b)

Figure 3.4. Steps of multigroup SEM to test whether the associations between classroom goal structure and the various outcome differ between differently motivated students (correlations and control variables not shown). For the first step in multigroup SEM, all structural coefficients (regression paths, correlations, means, and intercepts) are freely estimated across the two contrasted profile groups (a). In the second step, all structural parameters are freely estimated across the two profile groups but the regression coefficients from classroom mastery goal structure to the outcome is constrained to be equal for both profiles (b). The third step compares the change in model fit between steps 1 and 2. If the change in model fit is not statistically significant, this suggests that forcing the effect of mastery goal structure to be the same across the groups does not worsen the model fit. In contrast, if the change in model fit between steps 1 and 2 is statistically significant, this indicates that constraining the regression path to be the same across the groups worsens the model fit. This suggests that the estimated effect of classroom goal structure is different for the different achievement goal profile groups. Steps 1 through 3 are conducted separately for constraining mastery goal structure's and performance-approach goal structure's regression coefficients as well as with separate models using L1 and L2 measures of classroom goal structure.



(a)



(b)

Figure 3.5. Multigroup SEM results for *mastery goals perspective* (a) and *revised goals perspective* (b) profile groups when structural parameters were allowed to be freely estimated between the two groups (Profiles 1 and 4, respectively). Statistically significant ($p < .05$) unstandardized regression coefficients and covariances are reported.

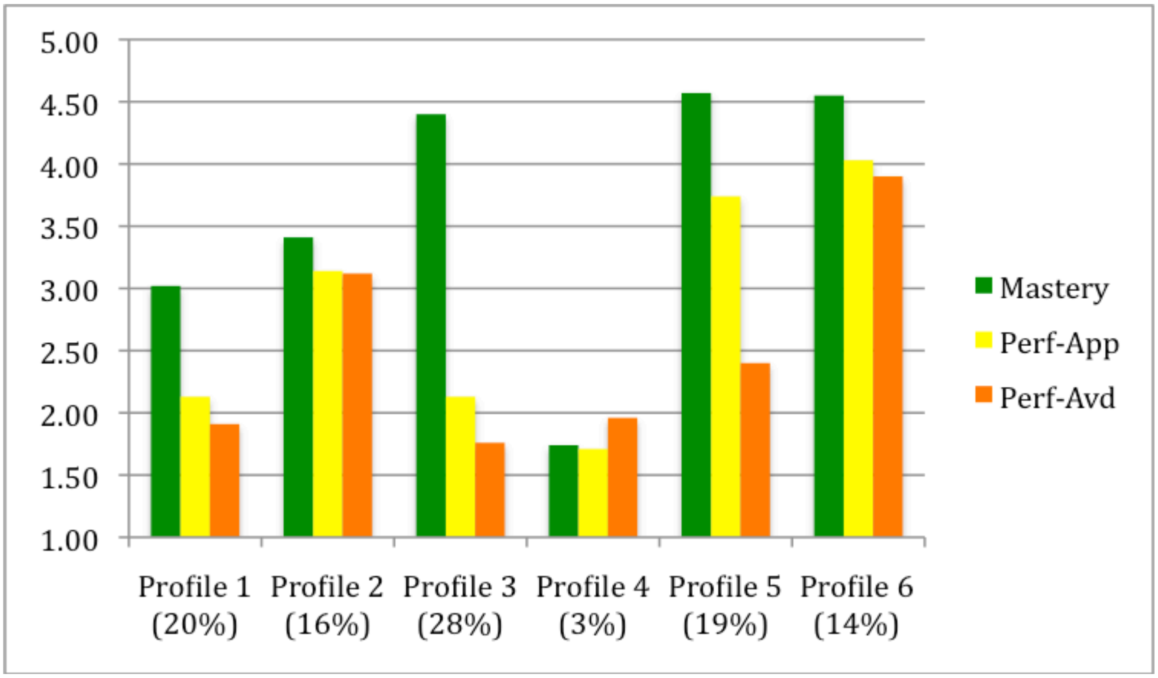
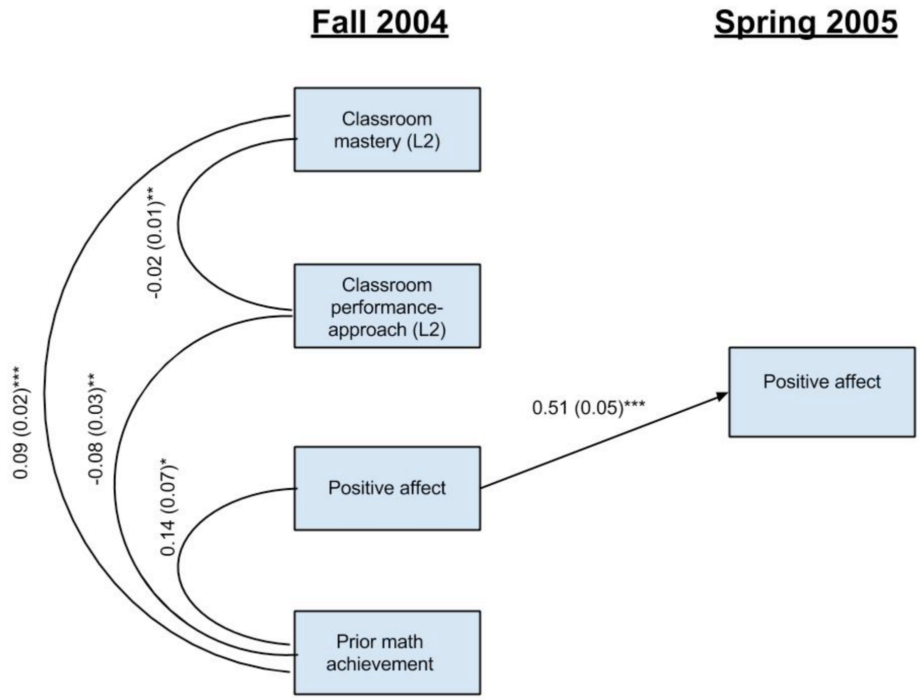
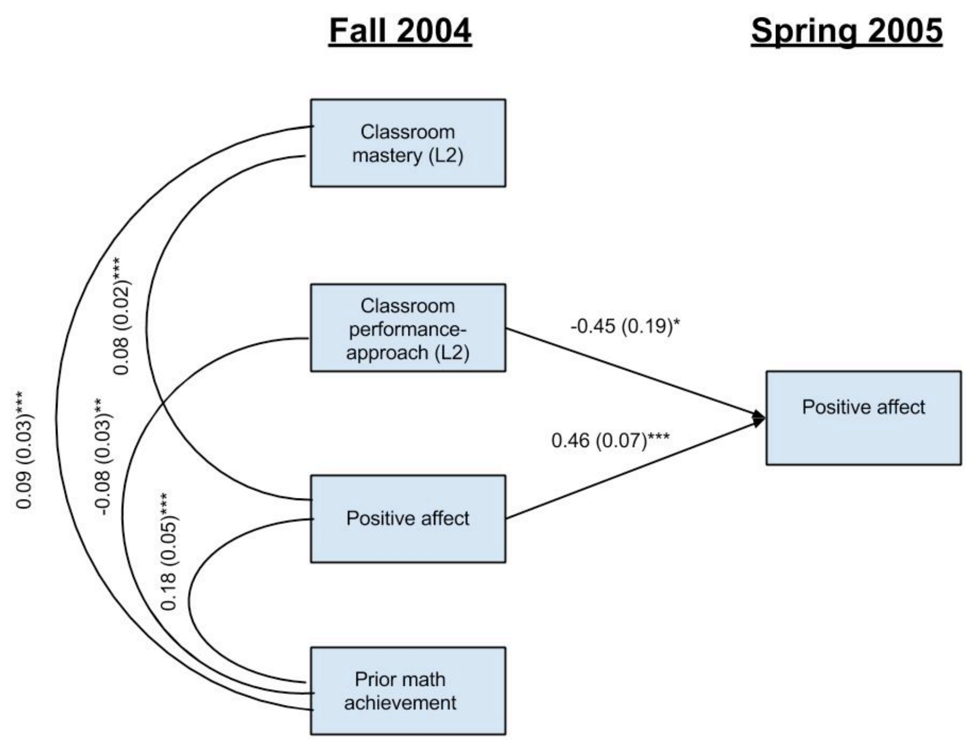


Figure 3.6. Latent profile groups of students based on their personal achievement goals for mathematics for Study 3's sample.



(a)



(b)

Figure 3.7. Multigroup SEM results for *mastery goals perspective* (a) and *revised goals perspective* (b) profile groups when structural parameters were allowed to be freely estimated between the two groups (Profiles 3 and 5, respectively). Statistically significant ($p < .05$) unstandardized regression coefficients and covariances are reported.

Table 3.1

Sample 2 descriptives (N = 2,520 seventh and eighth grade students in 157 mathematics classrooms)

	Mean	SD	Min	Max
Grade 7	7.53	0.5	7	8
Male	0.48	0.5	0	1
Hispanic	0.70	0.46	0	1
Math course grade	3.20	1.33	1	5
Prior math achievement (Spring 2005)	346.83	62.50	212	600
Math achievement (Spring 2006)	345.91	58.24	199	600
General 7th math	0.48	0.50	0	1
General 8th math	0.32	0.47	0	1
Algebra	0.20	0.40	0	1
Geometry	0.01	0.10	0	1
Personal goals (Fall 2005)				
Mastery	3.79	0.91	1	5
Performance-approach	2.48	1.07	1	5
Performance-avoidance	2.20	0.99	1	5
Classroom goal structure (Fall 2005)				
Mastery	4.12	0.75	1	5
Performance-approach	2.29	1.05	1	5
Help seeking (Spring 2006)				
Teacher	3.52	1.30	1	5
Peer	3.65	1.19	1	5
Expedient	2.58	1.24	1	5
Instrumental	3.87	1.09	1	5
Avoidant	2.30	1.24	1	5
Positive affect	2.54	0.97	1	5
Negative affect	2.99	0.76	1	5
Self-efficacy	3.31	0.91	1	5
Interest	2.56	1.17	1	5

Table 2.2

Correlations for Study 2's sample

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Classroom goals																	
1. Mastery (L2)	---																
2. Perf-Approach (L2)	-0.08***	---															
3. Mastery (L1)	0.37***	-0.03	---														
4. Perf-Approach (L1)	-0.03	0.34***	0.00	---													
Personal goals																	
5. Mastery	0.20***	0.05**	0.59***	0.13***	---												
6. Perf-Approach	0.08***	0.27***	0.16***	0.65***	0.30***	---											
7. Perf-Avoidance	0.05**	0.25***	0.04*	0.58***	0.12***	0.62***	---										
Outcomes																	
8. Positive affect	0.22***	0.01	0.26***	0.06**	0.35***	0.16***	0.05*	---									
9. Negative affect	-0.16***	0.07***	-0.16***	0.10***	-0.20***	0.03	0.15***	-0.49***	---								
10. Self-efficacy	0.11***	-0.09***	0.25***	0.02	0.31***	0.09***	-0.08***	0.43***	-0.34***	---							
11. Interest	0.17***	0.00	0.25***	0.09***	0.39***	0.18***	0.03	0.76***	-0.49***	0.55***	---						
12. Teacher HS	0.15***	-0.06**	0.25***	-0.05*	0.27***	0.02	-0.08***	0.46***	-0.34***	0.42***	0.41***	---					
13. Peer HS	0.09***	-0.07***	0.22***	-0.04	0.23***	0.02	-0.03	0.23***	-0.13***	0.25***	0.20***	0.35***	---				
14. Expedient HS	-0.04	0.07***	-0.05*	0.20***	-0.06**	0.17***	0.21***	-0.09***	0.22***	-0.04	-0.08***	-0.14***	-0.05**	---			
15. Instrumental HS	0.12***	-0.08***	0.30***	-0.01	0.27***	0.04*	-0.02	0.26***	-0.15***	0.31***	0.25***	0.33***	0.30***	-0.07***	---		
16. Avoidant HS	-0.05**	0.07***	-0.11***	0.12***	-0.12***	0.07***	0.15***	-0.20***	0.29***	-0.22***	-0.18***	-0.40***	-0.17***	0.22***	-0.18***	---	
17. Math CST	0.13***	-0.09***	0.10***	-0.05**	0.07***	-0.02	-0.08***	0.10***	-0.16***	0.36***	0.24***	0.08***	0.05*	-0.04*	0.07***	-0.11***	---
18. Math grade	0.06*	-0.00	0.14***	-0.04	0.14***	0.02	-0.07**	0.24***	-0.27***	0.37***	0.35***	0.23***	0.14***	-0.04	0.12***	-0.18***	0.58***

Note. * $p < 0.05$ ** $p < .01$ * $p < .001$. Classroom and personal goals measured in the Fall. Outcomes of interest measure in the Spring. HS = help seeking. CST = math scores California Standards Test.

Table 3.3

Model fit values for different class solutions

Number of classes	BIC	CAIC	AWE	VLMR
3	19701.89	19715.89	19853.54	< .001
4	19548.16	19566.16	19743.14	< .001
5	19385.59	19407.59	19623.89	< .001
6	19255.74	19281.74	19537.37	< .01
7	19153.70	19183.70	19478.66	0.05
8	19117.13	19151.13	19485.42	0.11

Note. BIC = Bayes information Criterion; CAIC = Consistent Akaike's Information Criterion; AWE = Approximate Weight of Evidence Criterion; VLMR = Vuong Lo-Mendell Rubin likelihood test. Model entropy for the 6-class solution was 0.72.

Table 3.4

Average scale scores for students' personal achievement goals for mathematics by profile membership (N = 2,520 7th and 8th grade students)

Profile	N	%	Mastery	Perf-App	Perf-Avd
1. Mastery goals perspective	631	25.04	4.03	1.48	1.34
2. Medium mastery-differentiated	783	31.07	3.71	2.46	2
3. High non-differentiated	269	10.68	4.29	4.2	3.86
4. Revised goals perspective	270	10.71	4.31	3.82	2.26
5. Medium non-differentiated	363	14.41	3.69	2.66	3.28
6. Low mastery-differentiated	204	8.1	2.26	1.33	1.39

Table 3.5

Direct effects OLS regression models with individual student perceptions of classroom goal structure (L1) predicting to student outcomes measured in the Spring (N = 2,520 7th and 8th grade students)

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
Classroom mastery (L1)	0.07***	-0.06**	-0.06	0.23***	0.14***	0.07**	0.01	0.12***	0.01	-0.05*	0.04*
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Classroom p-app (L1)	-0.02	0.08***	0.14***	-0.02	-0.03	-0.04	0.03	-0.02	0.01	0.03	0.01
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)
Prior CST	0.16***	-0.05**	0.03	0.03	0.05*	0.03	0.08**	0.46***	0.48***	-0.04*	0.03
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)
Fall measure	0.50***	0.28***	0.29***	0.23***	0.30***	0.43***	0.64***			0.42***	0.55***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)			(0.02)	(0.02)
Constant	1.25***	1.48***	1.74***	1.49***	1.42***	1.06***	0.52***	1.78***	-0.10	1.98***	0.74**
	(0.12)	(0.12)	(0.15)	(0.13)	(0.12)	(0.12)	(0.09)	(0.15)	(0.15)	(0.12)	(0.12)

Note. Standardized regression coefficients. Standard errors in parentheses. Clustered standard errors used to take into account of students nested in 157 math classrooms. HS = help seeking. Students' standardized mathematics achievement as measured by the CSTs were standardized within math test type.

Table 3.6

Direct effects OLS regression models with shared student perceptions of classroom goal structure (L2) predicting to student outcomes measured in the Spring (N = 2,520 7th and 8th grade students)

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
Classroom mastery (L2)	0.08	-0.01	-0.07	0.08***	0.05*	0.05*	0.01	0.06	-0.04	-0.06*	0.06*
	(-0.06)	(0.02)	(0.09)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)
Classroom p-app (L2)	-0.11*	0.05**	0.12	-0.07***	-0.04*	-0.05*	-0.01	0.05	0.04	0.02	0.00
	(0.05)	(0.02)	(0.08)	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.07)	(0.03)	(0.03)
Prior CST	0.13***	-0.05**	0.02	0.02	0.05*	0.02	0.07***	0.47***	0.49***	-0.04	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.06)	(0.02)
Fall measure	0.56***	0.30***	0.31***	0.29***	0.34***	0.44***	0.65***			0.42***	0.55***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)			(0.02)	(0.02)
Constant	1.33***	1.20***	1.73***	1.66***	1.53***	0.91*	0.57	1.21	0.38	3.10***	0.09
	(0.29)	(0.36)	(0.42)	(0.34)	(0.32)	(0.36)	(0.34)	(0.69)	(0.79)	(0.46)	(0.44)

Note. Standardized regression coefficients. Standard errors in parentheses. Clustered standard errors used to take into account of students nested in 157 math classrooms. HS = help seeking. Students' standardized mathematics achievement as measured by the CSTs were standardized within math test type.

Table 3.7

Chi-square difference tests for the multigroup SEM testing whether the regression coefficient for L2 performance-approach goal structure predicting to end-of-the-year outcomes differ between Profiles 1 and 4

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.35	3.88	2.08	2.83	0.01	0.34	0.01	20.10	0.08	1.04	0.20
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	$p < .0045$	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator. HS = help seeking.

Table 3.8

Study 3 sample descriptives (N = 1,287 7th and 8th grade students in 103 math classrooms)

	Mean	SD	Min	Max
Grade	7.45	0.50	7	8
Male	0.48	0.50	0	1
Hispanic	0.71	0.46	0	1
English language learner	0.51	0.50	0	1
State standardized math achievement				
Spring 2004	346.08	59.23	215	582
Spring 2005	350.38	59.04	212	600
Spring 2006	341.85	55.58	206	569
General 7th math	0.55	0.50	0	1
General 8th math	0.27	0.44	0	1
Algebra	0.17	0.37	0	1
Geometry	0.01	0.11	0	1
Personal goals (Fall 2004)				
Mastery (α = 0.87)	3.95	0.86	1	5
Performance-approach (α = 0.84)	2.87	1.07	1	5
Performance-avoidance (α = 0.78)	2.45	1.02	1	5
Classroom goal structure (Fall 2004)				
Mastery (α = 0.75)	4.24	0.71	1	5
Performance-approach (α = 0.82)	2.54	1.03	1	5
Outcomes (Spring 2005)				
Teacher HS	3.54	1.28	1	5
Peer HS	3.68	1.19	1	5
Expedient HS	2.67	1.29	1	5
Instrumental HS	3.91	1.08	1	5
Avoidant HS	2.27	1.24	1	5
Positive affect (α = 0.88)	2.58	0.96	1	5
Negative affect (α = 0.61)	2.99	0.74	1	5
Self-efficacy (α = 0.84)	3.29	0.92	1	5
Interest (α = 0.96)	2.62	1.20	1	5
Math course grade	3.24	1.32	1	5
Outcomes (Spring 2006)				
Teacher HS	3.51	1.26	1	5
Peer HS	3.64	1.18	1	5
Expedient HS	2.53	1.22	1	5
Instrumental HS	3.86	1.07	1	5
Avoidant HS	2.39	1.24	1	5
Positive affect (α = 0.89)	2.43	0.96	1	5
Negative affect (α = 0.60)	3.00	0.76	1	5
Self-efficacy (α = 0.84)	3.27	0.89	1	5
Interest (α = 0.95)	2.49	1.12	1	5
Math course grade	3.32	1.32	1	5

Note. Information on grade level and math course type taken assessed in Spring 2005. HS = help seeking. Math course grade is on a 5-point scale (1 = F; 5 = A).

Table 3.9

Correlations for Study 3's sample and short-term outcomes (Spring 2005)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Classroom goals																	
1. Mastery (L2)	---																
2. Perf-Approach (L2)	-0.27***	---															
3. Mastery (L1)	0.42***	-0.11***	---														
4. Perf-Approach (L1)	-0.09**	0.33***	0.05	---													
Personal goals																	
5. Mastery	0.24***	-0.01	0.64***	0.14***	---												
6. Perf-Approach	0.03	0.23***	0.21***	0.62***	0.34***	---											
7. Perf-Avoidance	-0.03	0.18***	0.06*	0.54***	0.12***	0.50***	---										
Outcomes																	
8. Positive affect	0.19***	-0.02	0.27***	0.07*	0.33***	0.16***	0.03	---									
9. Negative affect	-0.17***	0.08**	-0.15***	0.06*	-0.14***	-0.03	0.10***	-0.48***	---								
10. Self-efficacy	0.15***	-0.05	0.23***	0.02	0.30***	0.17***	-0.04	0.50***	-0.34***	---							
11. Interest	0.19***	-0.04	0.23***	0.07*	0.32***	0.17***	-0.04	0.80***	-0.47***	0.58***	---						
12. Teacher HS	0.14***	-0.06*	0.31***	0.02	0.32***	0.11***	-0.01	0.48***	-0.30***	0.44***	0.44***	---					
13. Peer HS	0.13***	-0.05	0.23***	0.03	0.24***	0.07*	0.02	0.23***	-0.04	0.15***	0.19***	0.33***	---				
14. Expedient HS	-0.09***	0.06*	-0.09***	0.16***	-0.08**	0.08**	0.16***	-0.08**	0.19***	-0.08**	-0.11***	-0.08**	0.05	---			
15. Instrumental HS	0.10***	-0.02	0.28***	0.03	0.28***	0.08**	0.03	0.29***	-0.09**	0.23***	0.27***	0.37***	0.31***	0.05	---		
16. Avoidant HS	-0.10***	0.10***	-0.16***	0.13***	-0.17***	0.07*	0.19***	-0.20***	0.24***	-0.21***	-0.20***	-0.41***	-0.13***	0.24***	-0.11***	---	
17. Math CST	0.26***	-0.18***	0.15***	-0.11***	0.17***	0.02	-0.10***	0.19***	-0.18***	0.41***	0.30***	0.12***	0.08**	-0.10***	0.03	-0.14***	---
18. Math grade	0.23***	-0.19***	0.18***	-0.10**	0.17***	-0.01	-0.13***	0.32***	-0.26***	0.44***	0.42***	0.26***	0.08*	-0.10**	0.07*	-0.20***	0.61***

Note. * $p < 0.05$ ** $p < .01$ * $p < .001$. Classroom and personal goals measured in Fall 2004. Outcomes of interest measure in Spring 2005. HS = help seeking. CST = math scores California Standards Test.

Table 3.9

Correlations for Study 3's sample and short-term outcomes (Spring 2005)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Classroom goals																	
1. Mastery (L2)	---																
2. Perf-Approach (L2)	-0.27***	---															
3. Mastery (L1)	0.42***	-0.11***	---														
4. Perf-Approach (L1)	-0.09**	0.33***	0.05	---													
Personal goals																	
5. Mastery	0.24***	-0.01	0.64***	0.14***	---												
6. Perf-Approach	0.03	0.23***	0.21***	0.62***	0.34***	---											
7. Perf-Avoidance	-0.03	0.18***	0.06*	0.54***	0.12***	0.50***	---										
Outcomes																	
8. Positive affect	0.19***	-0.02	0.27***	0.07*	0.33***	0.16***	0.03	---									
9. Negative affect	-0.17***	0.08**	-0.15***	0.06*	-0.14***	-0.03	0.10***	-0.48***	---								
10. Self-efficacy	0.15***	-0.05	0.23***	0.02	0.30***	0.17***	-0.04	0.50***	-0.34***	---							
11. Interest	0.19***	-0.04	0.23***	0.07*	0.32***	0.17***	-0.04	0.80***	-0.47***	0.58***	---						
12. Teacher HS	0.14***	-0.06*	0.31***	0.02	0.32***	0.11***	-0.01	0.48***	-0.30***	0.44***	0.44***	---					
13. Peer HS	0.13***	-0.05	0.23***	0.03	0.24***	0.07*	0.02	0.23***	-0.04	0.15***	0.19***	0.33***	---				
14. Expedient HS	-0.09***	0.06*	-0.09***	0.16***	-0.08**	0.08**	0.16***	-0.08**	0.19***	-0.08**	-0.11***	-0.08**	0.05	---			
15. Instrumental HS	0.10***	-0.02	0.28***	0.03	0.28***	0.08**	0.03	0.29***	-0.09**	0.23***	0.27***	0.37***	0.31***	0.05	---		
16. Avoidant HS	-0.10***	0.10***	-0.16***	0.13***	-0.17***	0.07*	0.19***	-0.20***	0.24***	-0.21***	-0.20***	-0.41***	-0.13***	0.24***	-0.11***	---	
17. Math CST	0.26***	-0.18***	0.15***	-0.11***	0.17***	0.02	-0.10***	0.19***	-0.18***	0.41***	0.30***	0.12***	0.08**	-0.10***	0.03	-0.14***	---
18. Math grade	0.23***	-0.19***	0.18***	-0.10**	0.17***	-0.01	-0.13***	0.32***	-0.26***	0.44***	0.42***	0.26***	0.08*	-0.10**	0.07*	-0.20***	0.61***

Note. * $p < 0.05$ ** $p < .01$ * $p < .001$. Classroom and personal goals measured in Fall 2004. Outcomes of interest measure in Spring 2005. HS = help seeking. CST = math scores California Standards Test.

Table 3.11

Model fit values for difference class solutions

Number of Classes	BIC	CAIC	AWE	VLMR
3	10262.95	10276.95	10405.19	< .01
4	10203.75	10221.75	10386.63	< .05
5	10155.35	10177.35	10378.87	0.07
6	10124.89	10150.89	10389.05	< .05
7	10112.83	10142.82	9378.42	0.31

Note. BIC = Bayes information Criterion; CAIC = Consistent Akaike's Information Criterion; AWE = Approximate Weight of Evidence Criterion; VLMR = Vuong Lo-Mendell Rubin likelihood test. Model entropy for the 6-class solution was 0.71.

Table 3.12

Average scale scores for students' personal achievement goals by profile membership (N = 1,287 7th and 8th grade students)

Profile	N	%	Mastery	Perf-App	Perf-Avd
1. Medium mastery-differentiated	255	19.81	3.02	2.13	1.91
2. Medium non-differentiated	212	16.47	3.41	3.14	3.12
3. Mastery goals perspective	357	27.74	4.40	2.13	1.76
4. Low non-differentiated	34	2.64	1.74	1.71	1.96
5. Revised goals perspective	244	18.96	4.57	3.74	2.40
6. High non-differentiated	185	14.38	4.55	4.03	3.90

Table 3.13

Direct effects OLS regression models with individual student perceptions of classroom goal structure (L1) predicting to student outcomes measured in the Spring 2005 (N = 1,287 7th and 8th grade students)

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
Classroom mastery (L1)	0.06*	-0.11***	-0.08**	0.23***	0.17***	0.14***	-0.03	0.13***	-0.02	-0.05	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Classroom p-app (L1)	0.00	0.09**	0.10***	0.00	0.03	0.02	0.03	-0.05*	-0.01	0.01	0.02
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	-0.03	(0.02)	(0.03)	(0.03)
Prior CST	0.17***	-0.04	-0.05	-0.04	0.03	0.03	0.06*	0.48*	0.66***	-0.05	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)	(0.03)	(0.03)
Fall measure	0.45***	0.24***	0.25***	0.18***	0.22***	0.37***	0.63***			0.39***	0.50***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)			(0.03)	(0.03)
Constant	0.34	2.06***	2.10***	1.79***	1.16***	0.53*	0.43*	1.78***	1.13***	2.98***	0.60*
	(0.24)	(0.26)	(0.25)	(0.30)	(0.24)	(0.23)	(0.21)	(0.23)	(0.15)	(0.32)	(0.24)

Note. Standardized regression coefficients. Standard errors in parentheses. Clustered standard errors used to take into account of students nested in 97 math classrooms. HS = help seeking. Students' standardized mathematics achievement, as measured by the CSTs, were standardized within math test type.

Table 3.14

Direct effects OLS regression models with individual student perceptions of classroom goal structure (L1) predicting to student outcomes measured in the Spring 2006 (N = 1,287 7th and 8th grade students)

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
Classroom mastery (L1)	0.04	-0.06*	-0.10***	0.19***	0.14***	0.09***	-0.07*	0.11**	0.00	0.00	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Classroom p-app (L1)	-0.04	0.07*	0.10***	-0.04	-0.01	0.00	0.02	0.00	0.05*	0.07**	0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(.03)	(.03)	(0.04)	(0.02)	(0.03)	(0.03)
Prior CST	0.15***	-0.08*	0.02	0.08**	0.10***	0.03	0.05*	0.42***	0.47***	-0.05	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)
Fall measure	0.31***	0.15***	0.21***	0.15***	0.17***	0.30***	0.48***			0.19***	0.32***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(.03)	(0.03)			(0.03)	(0.03)
Constant	1.43***	2.29***	1.87***	1.55***	1.17***	1.10***	0.30***	1.87***	-0.13	3.30***	1.31***
	(0.22)	(0.27)	(0.23)	(0.29)	(0.25)	(0.25)	(0.03)	(0.24)	(0.18)	(0.29)	(0.25)

Note. Standardized regression coefficients. Standard errors in parentheses. Clustered standard errors used to take into account of students nested in 97 math classrooms. HS = help seeking. Students' standardized mathematics achievement, as measured by the CSTs, were standardized within math test type.

Table 3.15

Direct effects OLS regression models with shared student perceptions of classroom goal structure (L2) predicting to student outcomes measured in the Spring 2005 (N = 1,287 7th and 8th grade students)

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
Classroom mastery (L2)	0.01	-0.04	-0.05	0.10*	0.09*	0.05	0.01	0.12*	-0.10**	-0.09*	0.07
	(0.11)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)	(0.03)	(0.04)	(0.04)
Classroom p-app (L2)	-0.03	0.04	0.02	0.01	-0.01	-0.03	-0.02	-0.08	0.02	0.01	-0.01
	(.09)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.04)	(0.03)	(0.04)
Prior CST	0.00***	-0.04	-0.05	-0.03	0.02	0.02	0.05	0.45***	0.69***	-0.03	0.01
	(0.00)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Fall measure	0.52***	0.27***	0.27***	0.23***	0.23***	0.42***	0.62***			0.39***	0.51***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)			(0.03)	(0.03)
Constant	0.61	1.83**	2.40***	1.50*	0.86	0.74	0.41	1.23	1.29*	3.79***	0.05
	(0.58)	(0.70)	(0.51)	(0.64)	(0.70)	(0.72)	(0.63)	(0.99)	(0.60)	(0.71)	(0.72)

Note. Standardized regression coefficients. Standard errors in parentheses. Clustered standard errors used to take into account of students nested in 97 math classrooms. HS = help seeking. Students' standardized mathematics achievement, as measured by the CSTs, were standardized within math test type.

Table 3.16

Direct effects OLS regression models with shared student perceptions of classroom goal structure (L2) predicting to student outcomes measured in the Spring 2006 (N = 1,287 7th and 8th grade students)

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
Classroom mastery (L2)	-0.01	-0.02	-0.01	0.10**	0.08*	0.04	-0.05	0.06	0.11	0.02	0.00
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.15)	(0.03)	(0.04)
Classroom p-app (L2)	-0.04	-0.01	0.04	0.01	0.02	-0.02	-0.05*	-0.05	0.21	0.06	-0.06
	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)	0.03	(0.04)	(0.12)	(0.03)	(0.04)
Prior CST	0.15***	-0.09**	0.01	0.08**	0.10***	0.03	0.05*	0.42***	0.47***	-0.05	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Fall measure	0.32***	0.17***	0.23***	0.19***	0.20***	0.34***	0.47***			0.20***	0.32
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)			(0.03)	(0.03)
Constant	2.00***	2.46***	1.43*	0.92	0.57	1.10	1.99***	2.09**	-0.99	2.77***	1.87**
	(0.50)	(0.59)	(0.61)	(0.67)	(0.56)	(0.63)	(0.48)	(0.78)	(0.80)	(0.57)	(0.59)

Note. Standardized regression coefficients. Standard errors in parentheses. Clustered standard errors used to take into account of students nested in 97 math classrooms. HS = help seeking. Students' standardized mathematics achievement, as measured by the CSTs, were standardized within math test type.

Table 3.17

Chi-square difference tests for the multigroup SEM testing whether the regression coefficient for L2 performance-approach goal structure predicting to short-term (Spring 2005) outcomes differ between Profiles 3 and 5

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	2.06	3.26	0.06	1.19	0.88	2.85	1.77	0.05	0.34	1.27	8.73
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	$p < .0045$

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator. HS = help seeking.

CHAPTER FOUR

Summary and Conclusion

Though much of educational research is concerned with the instructional context of the classroom, the socio-emotional and motivational climate set up by teachers is also important to consider. One common way used to describe classrooms is by the achievement goals they emphasize (Ames, 1992; Ames & Archer, 1988), and it has been shown that differences in these goals have motivational, behavioral, and achievement implications (for review, see Urdan, 2010). Within this dissertation, I am interested in: 1) how to measure the classroom goal structure using student surveys, 2) how perceived classroom goal structure are related to a variety of critical student outcomes, and 3) whether the perceived alignment or misaligment between the students' own goals and the classroom goals matters. To answer these questions, I used a large, rich source of data on student perceptions of classroom goal structure, their personal achievement goals for math, and various critical learning-related outcomes. Below I present results regarding the measurement of student perceptions of classroom goal structure and the alignment between classrooms' and students' goals. Following the summary of findings, I discuss larger overarching themes that emerged from the findings. Finally, I close with a discussion of new directions for research (both in general and for my own personal research) as informed by this dissertation.

Summary of Findings

Prior work examining differences between classrooms verify classroom goal structure measures at the student level (L1) only. For instance, they typically examine the classroom goal structure scales' reliability and model fit at the student level, and then aggregate student responses to the classroom level (L2) to examine differences between classrooms. In study 1, my co-authors and I examined whether student reports' of their math classrooms' goal structure (mastery, performance-approach, performance-avoidance) can also be verified at the classroom level (Lam, Ruzek, Schenke, Conley, & Karabenick, 2015). Using student survey responses (*N* = 1,406 seventh and eighth grade students in 188 mathematics classrooms), we employed three analytical approaches to examine the L2 properties of the Patterns of Adaptive Learning Survey's (PALS) classroom goal structure scales (Midgley et al., 2000). First, we calculated the intraclass correlation (ICC1) to examine the proportion of total variance explained by student membership in different classrooms. The ICC1 for mastery goal structure was highest with 11% of the variance attributable to classroom membership, whereas the ICC1 values for performance-approach and –avoidance was lower (5% and 6%, respectively). Next, we calculated ICC2 to evaluate the reliability of the classroom aggregate measures. Put differently, how reliable or how much noise does the classroom mean measures have? Compared to desirable ICC2 values of 0.70 or above, group-level reliability was 0.69 for mastery goal structure, 0.46 for performance-approach, and 0.54 for performance-avoidance. Lastly, we conducted a series of multilevel confirmatory factor analyses (MCFA) to examine loading patterns and model fit of each construct both within student reporters (L1) and between classrooms (L2). Similar to prior studies, we found adequate fit at the student level. However, only the performance-avoidance model represented the expected goal structure at the classroom level. Taken together, the results cast doubt on whether the L2 student-reported measures of classroom goal structure can reliably differentiate between classrooms along the classroom goal structure dimensions.

In study 2 (*N* = 2,520 seventh and eighth grade students in 157 math classrooms), I tested the matching hypothesis and examined whether the interplay between the classrooms' perceived goal structure and students' personal achievement goal orientation matter for a range of motivational, behavioral, and achievement outcomes. Study 3 (N = 1,287 seventh and eighth grade students in 103 mathematics classrooms) was a replication and longitudinal extension of study 2 by examining: 1) whether similar patterns of findings emerged with a different sample of middle school students, and 2) the long-term consequences measured one year after students have left their math classrooms. To capture students' multiple goals, the studies employed latent profile analysis to examine the different patterns of students' personal achievement goals (mastery, performance-approach, and performance-avoidance). Then, a series of multiple group structural equation models tested whether classroom goal structures have differential effects depending on students' personal achievement goal profiles.

Both studies 2 and 3 found six motivational profiles within the samples of middle school students, with similar profiles appearing across both samples of students. Across both studies, both individual perceptions (L1) and classroom aggregate measures (L2) of mastery goal structure were associated with adaptive changes in student outcomes (such as achievement and help seeking) whereas performance-approach goal structure was associated with maladaptive changes for both short- and long-term outcomes (such as avoidant and expedient help seeking). In addition, the pattern of findings indicated that L1 measures were stronger predictors of the various types of help-seeking behaviors and math course grades than the L2 measures. Results provide evidence for the matching hypothesis, wherein students who endorsed both mastery and performance-approach goals benefited in higher grades in comparison to students who solely endorsed mastery goals, but only in classrooms collectively rated as emphasizing performance-approach goals. However, another finding conflicts with the matching hypothesis. Students who were both mastery and performance-approach oriented fared worse and reported lower positive affect than students who were highly mastery oriented in classrooms collectively rated as emphasizing performance-approach goals.

Themes

Each study within this dissertation answered specific questions regarding the nature of perceived classroom goal structure. Taken together, the three studies provide insights into the measurement of perceptions of classroom goal structure and the processes of influence beyond the individual research questions. These insights are discussed as two themes that may be informative for future research.

Capturing the Classroom Climate

The pattern of findings between the individual perceptions (L1) and the shared classroom aggregate (L2) measures were similarly predictive of the various individual student outcomes, supporting the use of self-report measures. Although the individual measures were stronger predictors of the various types of help-seeking behaviors and math course grades than the classroom aggregate measure, this suggests that student perceptions of the classroom are also important to consider. Indeed, findings from Study 1 suggest that, for this sample of students, student reports should not be aggregated to the classroom level. It is not surprising that a noisy measure lacking L2 reliability would be a weak predictor. Nonetheless, findings from both L1 and L2 measures tell the same story—perceptions of classroom mastery goal structure were associated with adaptive outcomes whereas perceptions of performance-approach goal structure were associated with undesirable outcomes. Taken together, these results provide some empirical evidence supporting the view by Kaplan and colleagues that the motivational climate has both an objective and more subjective component (Kaplan, Middleton, Urdan, & Midgley, 2002). The three studies together point to the need to better understand the sources of student-level and classroom-level variation in perceptions of classroom goal structure.

Though studies 2 and 3 conducted parallel analyses using both L1 and L2 measures of classroom goal structure, reliable and valid observational measures would be ideal to use in addition to self-report measures to better understand what is happening in classrooms. Some researchers have argued that there is an overreliance on students' perceptions of classroom goal structure in the field (Kaplan et al., 2002). Studies have demonstrated that students' motivational tendencies are related to their perception of the classroom (Kaplan et al., 2002), thus, it is difficult to make suggestions to educators and it is unclear how objective changes to the classroom (e.g., how a teacher sets up grading norms) will impact student outcomes. Research utilizing observational measures may suggest implementing changes in the classroom that can potentially influence a broader range of students, not just those who perceive a mastery-oriented or performance-approach classroom. Nonetheless, there is evidence that students' self-reports of classroom goal structure are systematically related to teacher practices based on classroom observations (Patrick, Anderman, Ryan, Edelin, & Midgley, 2001). There is a need for more research that uses multiple methods such as classroom observations, interviews, and stimulated recalls to triangulate and validate findings based on student perceptions (Urdan, 2004). Research in this direction would be very informative to researchers and practitioners alike to make direct recommendations for teacher practice.

Interplay between Person and Environment

Studies 2 and 3 examined the affordances and drawbacks of mastery and performance-approach goal structure and whether students' personal goal orientations moderate the associations between perceived classroom goal structure and a broad array of student outcomes.

The traditional mastery perspective predicts that students in mastery-oriented classrooms would benefit across all outcomes. In contrast, the revised goals perspective would predict that performance-approach goals would have additive, interactive, or specialized effects across the various outcomes (Muis, Ranellucci, Franco, & Crippen, 2013). Results from both studies provide strong evidence for the traditional mastery perspective. Perceptions of mastery goal structure was found to be equally beneficial for all students across the samples. In addition, performance-approach goal structure, in general, was associated with less self-reported adaptive types of help seeking and increased maladaptive types of help seeking.

It is interesting that the two findings for the match effect in studies 2 and 3 was with the L2 measure of classroom performance-approach, indicating that being in a classroom collectively rated as having a performance-approach emphasis differentially affected students. The first finding was that students reflective of the revised goals perspective (high mastery and performance-approach) benefited in higher math grades than their classmates who were solely focused on personal mastery goals, but only in classrooms collectively rated as having a performance-approach focus. Indeed, Senko and Miles (2008) found that mastery-oriented undergraduate students allocated their study efforts disproportionately to personally interesting material, which in turn predicted low grades in class. Although personal mastery goals are associated with the use of both shallow and deep learning strategies (Elliot, McGregor, & Gable, 1999; Greene & Miller, 1996; Wolters, Yu, & Pintrich, 1996), mastery-oriented students may be more interested in pursuing their own learning agendas, allocate their energy to topics of greater interest, and perhaps delve into topics tangential to the course's content. This type of effort may not be reflected in grades and may even hinder learning of the duller course material that may be emphasized on multiple-choice tests and assignments. This has been termed as the "achievement measure explanation", which attributes the weak association found between personal mastery goals and achievement in the literature to teachers' assessment procedures rather than the flaw of mastery goals (Senko & Miles, 2008). In contrast, it is thought that performance-approach students who share the teacher's learning agenda focus their study efforts on the topics deemed important by the teacher and therefore should perform better than mastery-oriented students. For instance, competitive students, who typically endorse personal performance-approach goals, may be watchful for cues in the classroom that can direct their studying efforts, such as teacher's stated task demands and hints about the importance of various topics during class discussions (Entwistle, 1988; Entwistle & Tait, 1990). However, this result must be interpreted with caution and must also be interpreted in the context from the direct effect model that showed that L2 performance-approach goal structure has an overall negative effect on self-efficacy beliefs and various adaptive forms of help seeking.

In contrast to the first finding, another finding from this dissertation demonstrated that a match between students and classrooms on the performance-approach goal dimension can also be detrimental. Students who endorsed both high mastery and performance-approach goals reported lower levels of positive affect than their mastery-oriented peers, but only in classrooms that were collectively rated as emphasizing performance-approach goals. Though the few extant studies testing the matching hypothesis usually focus on the match effect on achievement and interest (Lau & Nie, 2008; Murayama & Elliot, 2009), study 3 found that another consequence is the affect students reported experiencing in class. The pattern of results demonstrates the complexity of performance-approach goals. Similar to Murayama and Elliot's (2009) findings, the match effect was only observed for performance-approach goals. This illustrates personal performance-approach goals' varied profile: sometimes they are linked to positive outcomes, sometimes they produce null results, and sometimes they are linked to negative outcomes. These conflicting findings are likely due to a number of sources, and the results presented in this dissertation suggest that one such source may be the classroom goal structure.

Future work

This dissertation provides novel information on student perceptions of the classroom goal structure, individual differences in students' personal goal orientations, and the interplay between the student and classroom goals. It has also informed my thinking and new avenues of research both within and outside of achievement goal theory. In closing, I detail potentially fruitful areas for future research as well as directions where I see my research growing.

Using Student Surveys to Assess Classroom Climate

Researchers have noted the need for more research examining the sources of student-level and classroom-level variation in classroom goal structure. For example, Wolters (2004) recommended that future research clarify whether student-level differences stem from differences in teacher-student interactions or from basic beliefs held by the students that may color their perceptions of the classroom, such as beliefs about the nature of ability. My co-authors and I are now delving into this type of work (Schenke, Lam, Ruzek, Conley, Karabenick, & Eccles, 2015). We are currently exploring the heterogeneity of student perceptions of the socio-emotional classroom climate along three important dimensions (autonomy, emotional support, and competition) and examining: 1) the profiles of perception of the classroom, and 2) what predicts students' profile of perception. Specifically, we use latent profile analysis to capture the various shared patterns of perceptions of the classroom. Then, using these latent profiles, we examine whether there are systematic differences in perceptions of the math classrooms by gender, achievement levels, perceptions of their previous math teachers, and personal beliefs (self consciousness, self-efficacy, and anxiety). Taking into account that student perceptions of the classroom are heterogeneous, a latent profile approach can capture shared aspects of the perceived classroom climate when the classroom aggregate (L2) measure may not be very reliable. In addition, these analyses can help provide insight into sources of individual-level variation of classroom perceptions. Our preliminary findings show that different student characteristics are differentially related to perceptions of the classroom. Future research can examine additional sources of individual-level variation in perceptions of classroom goal structure. For example, differential treatment from the teacher or ability grouping within the classroom can explain the lack of agreement between student raters.

Another future direction is exploring the number of profiles of perceptions within classrooms and examining the implications of being in a classroom with homogenous or heterogeneous perceptions. One preliminary step we have taken is descriptively looking at the number of perception profiles as well as the different combination of profiles within a classroom (Schenke et al., 2015). Our next step is examining the distribution of such profiles within a classroom. For example, in classrooms A and B, there are two groups of students who either perceive the same classroom as highly competitive or highly emotionally supportive. However, the distribution of these perceptions differs between these two classrooms. In classroom A, the majority of the students view the classroom as being emotionally supportive and only a small minority of students view the classroom as being competitive. In contrast, half of the students in classroom B perceive it as being emotionally supportive whereas the other half perceive it as being competitive. Using a heterogeneity index, such as Simpson's D, that captures the distribution of perceptions (e.g., 90-10 vs. 50-50), we seek to examine the outcomes associated with being in a classroom where there is more agreement among students. On the other hand, what are the consequences of being in a classroom with less agreement or a more heterogeneous distribution of perceptions (for an example of an application of a heterogeneity index in the classroom, see Rjosk, Richter, Lüdtke, & Eccles, 2015)? We believe that these are two potentially interesting avenues to explore.

Achievement goal theory is one of many theories available to study the classroom learning environment. Although it would be ideal to employ MCFA in future studies to test the L2 validity of other classroom climate measures, most studies do not have the sample sizes needed to employ MCFA. Being cognizant of real world obstacles most studies of classroom climate must deal with, future work using student surveys to assess classroom climate can employ the other indices in Study 1, such as ICC1 and ICC2, to test the classroom-level properties of the various measures when MCFA is not possible. Another takeaway message for future research is the need to ensure that an adequate number of students are sampled within each classroom so that the classroom aggregate measure is reliable (i.e., higher ICC2).

Individual Differences in Student Motivation and Trajectories

As illustrated in studies 2 and 3, latent profile analysis provides a useful approach to studying individual differences in student motivation. This type of approach can also be applied to studying individual differences in longitudinal patterns or trajectories. For example, my co-authors and I are using latent class analysis to examine the various longitudinal trajectories for STEM and non-STEM career aspirations and examining whether there are gender and ethnic differences in these career aspirations (Safavian, Lam, Lauermann, Banerjee, & Eccles, 2015). We are examining the development of career aspirations from adolescence to early adulthood (grades 7, 10, 12, and 6 years after high school) and have identified three longitudinal patterns: those who consistently aspired to non-STEM careers; those who aspired for STEM-related careers (physical sciences, mathematics, engineering, and technology [PMET]) in-and-throughout adolescence but began shifting to non-STEM by adulthood; and those who aspired for medical-life science careers but began shifting to non-STEM by adulthood. Pattern-centered approaches, in general, can reveal different meaningful subgroups when sample means may overlook interesting configurations of factors as they reside within individuals.

Person x Environment Fit or Heterogeneity of Treatment Effects

Studies 2 and 3 used students' responses to classroom goal structure items given in the Fall, approximately three weeks into the school year. Students' reports of their classroom in the Spring should be better informed than their reports in the Fall. However, I am interested in the interplay between the students' perceptions of classroom goals and students' goals when they first enter the classroom (Fall) and how the students' experiences of perceived (mis)match over the year relate to changes. Noteworthy, Fall and Spring perceptions of classroom goal structure are moderately associated with one another (*r* = approximately 0.50), suggesting that (1) there were "real" changes in the classrooms between the beginning and end of the school year, or (2) other phenomena were causing changes in students' perceptions. Ideally, reliable and valid observational measures of these classrooms also taken in the Fall and Spring would be available to compare against the student reports. Example analyses to be conducted include comparing the correlation between the Fall and Spring observational measures to the correlation between Fall and Spring student perceptions, comparing the mean and standard deviation of student reports of their math classroom and seeing how they relate to the observational measure, and testing whether the (mis)alignment between students' personal goals and the observational measure of classroom goal structure matters. This type of information would allow examination of how the student perceived environment and the “objective” observed environment interacts with personal dispositions in shaping students’ well being.

In addition, it would be interesting for future research to employ mixed methods to examine both classroom characteristics and student characteristics. For example, such research can use surveys to identify different student motivational profiles. Observational methods then can be used to: 1) assess classroom policies and instructional moves by the teacher that communicate the classroom goals, and 2) see how the differently motivated students react to the same observed classroom practices. Survey measures assessing a swath of outcomes can help validate the findings from the classroom observations in examining whether students react differently. In addition, interview methods can also directly ask students about the goals emphasized in their classrooms, the teacher practices or classroom policies that informed their perceptions of the classroom goals, and how those practices influenced their thinking about their own learning.

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Appendix A

Personal Goal Orientation – Mastery Approach (PALS; MIdgley et al. 2010)

Learning a lot of new things is what is important to me in math.
One of my main goals in math is to improve my skills.
My main goal in math is to learn as much as I can.
Really understanding my math work is important to me.
Learning new skills in math is one of my goals.

Personal Goal Orientation – Performance Approach (PALS; MIdgley et al. 2010)

In math, doing better than other students is important to me.
My goal in math is to look smarter than other students.
One of my goals is to show others that math is easy for me.
It's important to me that others think I am good at doing math.
My goal in math is to do better than other students.

Personal Goal Orientation – Performance Avoid (PALS; MIdgley et al. 2010)

My goal is to keep others from thinking I'm not smart in math.
It's important to me that I don't look stupid in math class.
An important reason I do my math work is so that I don't embarrass myself.
I do my math work so that my teacher doesn't think I know less than others.
My goal in math is to avoid looking like I can't do my work.

Classroom Goal Structure – Mastery Approach (PALS; MIdgley et al. 2010)

In our math class, it's OK to make mistakes as long as you are learning.
In our math class it's important to understand the work, not just memorize it.
In our math class, really understanding the material is the main goal.
In our math class, learning new ideas and concepts is very important.
In our math class, how much you improve is really important.

Classroom Goal Structure – Performance Approach (PALS; MIdgley et al. 2010)

In our math class, it's important to get higher scores on tests than other students.
In our math class, it's important to get more right answers than other students.
In our math class, getting better grades than other students is the main goal.
In our math class, it's important to show how smart you are compared to others.
In our math class, it's important to look like you can do the work.

Classroom Goal Structure – Performance Avoidance (PALS; MIdgley et al. 2010)

In our math class, it's important that you don't make mistakes in front of everyone.
In our math class, it's important not to look dumb.
In our math class, showing others that you are not bad in math is really important.
In our math class, it's important not to do worse than other students.
In our math class, one of the main goals is to avoid looking like you can't do the work.

Affect in School – Positive (PANAS-X; Watson & Clark, 1994)

How often do you feel happy in your math class?
How often do you feel enthusiastic in your math class?
How often do you feel excited in your math class?
How often do you feel interested in your math class?

Affect in School – Negative (PANAS-X; Watson & Clark, 1994)

How often do you feel anxious in your math class?
How often do you feel bored in your math class?
How often do you feel exhausted in your math class?
How often do you feel irritated in your math class?

Math Efficacy (PALS; MIdgley et al. 2010)

How certain are you that you can learn everything taught in math?
How sure are you that you can do even the most difficult homework problems in math.
How confident are you that you can do all the work in math class, if you don't give up.
How confident are you that you can do even the hardest work in your math class.

Subjective Task Value: Interest (Eccles et al., 1993)

I enjoy the subject of math.
I am fascinated by math.
I like math.
I enjoy doing math.
Math is exciting to me.
How much do you like doing math?

Help Seeking (adapted from Karabenick, 2004)

If I didn't understand something in this math class I would ask my teacher for help. *(formal help seeking)*
If I didn't understand something in this math class I would ask another student in class for help. *(peer help seeking)*
Even if I couldn't finish an assignment for this math class, I wouldn't ask for help. *(avoidant help seeking)*
If I were to ask for help in this math class it would be to quickly get the answers I needed. *(expedient help seeking)*
If I were to ask for help in this math class it would be to learn how to do the problems. *(expedient help seeking)*

Appendix B

Study 2's chi-square difference tests based on log-likelihood values and scaling correction factors obtained from MLR estimator

Planned contrasts between *mastery goals perspective* and *revised goals perspective* (profiles 1 vs. 4)

Testing L1 classroom mastery goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.03	0.00	2.21	0.30	0.05	1.45	1.78	0.49	0.00	0.04	0.68
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom performance-approach goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.05	0.15	0.01	0.93	0.00	1.50	0.43	0.90	2.71	0.10	0.49
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom mastery goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.32	0.07	0.83	0.15	0.20	0.02	1.62	0.08	0.18	1.38	0.04
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Planned contrasts between *mastery goals perspective* and the *low non-differentiated* (profiles 1 vs. 6)

Testing L1 classroom mastery goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	1.65	0.56	6.31	3.06	0.18	0.39	0.02	0.01	0.96	0.03	0.06
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom performance-approach goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.58	0.31	0.14	0.00	2.33	0.06	0.00	1.65	3.46	1	0.00
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom mastery goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	2.98	0.01	0.02	0.28	0.27	0.01	1.56	0.81	1.64	0.02	0.44
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom performance-approach goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	1.82	0.26	0.12	0.55	0.24	0.56	0.53	1.37	0.12	0.35	0.03
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Planned contrasts between *high non-differentiated* and *revised goals perspective* (profiles 3 vs. 4)

Testing L1 classroom mastery goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.00	0.27	0.02	0.18	0.13	0.15	0.22	0.01	0.17	1.77	0.00
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom performance-approach goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.07	0.00	0.91	1.31	0.16	0.81	0.52	0.51	0.01	0.04	0.11
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom mastery goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.75	3.04	4.32	4.30	2.43	0.29	1.14	0.04	0.60	4.86	3.08
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom performance-approach goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.07	4.13	0.21	3.67	1.43	0.02	0.00	0.02	0.03	2.18	0.35
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Planned contrasts between *medium mastery-differentiated* and *medium non-differentiated* (profiles 2 vs. 5)

Testing L1 classroom mastery goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	5.83	0.08	2.21	0.40	0.12	2.27	0.51	2.37	0.00	0.61	0.47
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom performance-approach goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.03	0.00	0.37	1.17	0.79	0.01	4.00	0.60	0.60	0.98	0.13
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom mastery goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	5.38	0.06	0.05	3.24	0.73	0.00	2.60	1.84	0.50	0.16	1.54
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom performance-approach goal structure's regression coefficient predicting to end-of-the-school year outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.33	0.21	0.80	0.28	0.17	0.82	1.20	0.67	2.25	0.30	0.09
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Appendix C

Study 3's chi-square difference tests based on log-likelihood values and scaling correction factors obtained from MLR estimator

Planned contrasts between *mastery goals perspective* and *revised goals perspective* (profiles 3 vs. 5)

Testing L1 classroom mastery goal structure's regression coefficient predicting to short-term (Spring 2005) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.39	0.15	1.72	0.55	1.31	0.05	0.19	0.03	0.20	2.79	0.37
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom performance-approach goal structure's regression coefficient predicting to short-term (Spring 2005) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.63	0.06	1.51	0.33	0.29	1.51	0.70	3.43	0.48	0.03	0.79
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom mastery goal structure's regression coefficient predicting to short-term (Spring 2005) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	3.85	2.77	1.33	0.01	1.72	0.91	0.11	0.00	0.08	0.08	0.00
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom mastery goal structure's regression coefficient predicting to long-term (Spring 2006) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	3.03	0.12	0.24	2.52	0.21	0.04	1.32	1.28	0.84	1.30	1.78
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom performance-approach goal structure's regression coefficient predicting to long-term (Spring 2006) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.96	1.09	0.05	0.86	0.37	7.12	7.44	4.43	0.49	1.37	1.49
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom mastery goal structure's regression coefficient predicting to long-term (Spring 2006) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.97	0.51	4.13	0.52	0.05	0.02	0.31	1.83	0.85	0.86	0.01
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom performance-approach goal structure's regression coefficient predicting to long-term (Spring 2006) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.16	2.30	0.07	4.90	0.99	0.04	3.26	2.78	0.73	0.96	0.54
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Planned contrasts between *revised goals perspective* and *high non-differentiated* (profiles 5 vs. 6)

Testing L1 classroom mastery goal structure's regression coefficient predicting to short-term (Spring 2005) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.67	0.00	0.04	0.01	0.76	1.82	0.02	0.37	1.75	1.02	1.78
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom performance-approach goal structure's regression coefficient predicting to short-term (Spring 2005) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	1.49	0.75	0.00	0.89	0.54	0.05	0.20	0.37	0.12	0.35	0.19
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom mastery goal structure's regression coefficient predicting to short-term (Spring 2005) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	2.42	1.21	1.00	2.08	1.42	1.72	0.01	4.94	0.01	0.00	1.67
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom performance-approach goal structure's regression coefficient predicting to l short-term (Spring 2005) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	2.07	0.58	0.21	2.18	0.20	0.18	1.29	2.50	0.01	0.40	1.59
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom mastery goal structure's regression coefficient predicting to long-term (Spring 2006) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	1.12	1.37	0.42	0.55	4.63	0.00	0.79	1.80	0.06	0.24	1.04
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom performance-approach goal structure's regression coefficient predicting to long-term (Spring 2006) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	1.16	0.38	0.01	0.02	0.31	0.13	0.04	0.01	3.38	0.45	0.03
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom mastery goal structure's regression coefficient predicting to long-term (Spring 2006) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	1.19	0.87	0.24	0.19	0.30	0.00	0.01	0.63	0.00	0.24	0.23
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom performance-approach goal structure's regression coefficient predicting to long-term (Spring 2006) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.84	0.00	1.58	1.89	0.05	0.13	1.16	0.18	0.06	0.45	0.32
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Planned contrasts between *medium mastery-differentiated* and *mastery goals perspective* (profiles 1 vs. 3)

Testing L1 classroom mastery goal structure's regression coefficient predicting to short-term (Spring 2005) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.04	1.24	0.01	1.88	2.30	0.01	0.26	0.34	0.14	3.48	0.87
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom performance-approach goal structure's regression coefficient predicting to short-term (Spring 2005) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	1.61	0.47	0.03	2.65	0.66	0.47	1.19	0.61	2.38	2.37	0.48
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom mastery goal structure's regression coefficient predicting to short-term (Spring 2005) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	1.87	1.81	0.05	0.08	0.00	0.05	0.00	0.04	0.02	0.11	1.35
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom performance-approach goal structure's regression coefficient predicting to l short-term (Spring 2005) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.23	3.28	2.73	0.92	2.16	0.11	0.02	3.22	0.03	0.09	0.00
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom mastery goal structure's regression coefficient predicting to long-term (Spring 2006) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	1.99	1.22	0.00	0.02	1.44	3.22	0.20	1.17	0.27	2.39	0.15
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L1 classroom performance-approach goal structure's regression coefficient predicting to long-term (Spring 2006) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.27	0.52	2.11	0.78	0.02	0.80	3.53	3.71	0.10	0.14	1.34
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom mastery goal structure's regression coefficient predicting to long-term (Spring 2006) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.34	0.41	0.41	0.04	0.27	0.12	0.36	0.01	0.27	1.11	1.47
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.

Testing L2 classroom performance-approach goal structure's regression coefficient predicting to long-term (Spring 2006) outcomes

	Self-efficacy	Avoidant HS	Expedient HS	Instrumental HS	Peer HS	Teacher HS	Interest	Math Grade	Std. Math Ach.	Neg. Affect	Pos. Affect
TRd	0.34	0.41	0.41	0.04	0.27	0.12	0.36	3.41	0.60	1.11	1.47
df	1	1	1	1	1	1	1	1	1	1	1
corrected *p*-value	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note. Critical values for chi-square test with df = 1 at $p < .0045$ is 7.879. TRd = chi-square difference test calculated from the log-likelihood values and scaling correction factors obtained from MLR estimator.