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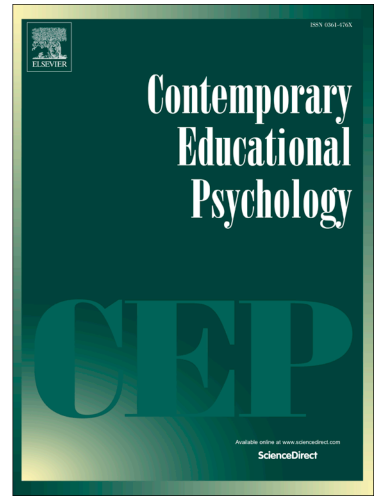

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Relations among Math Self Efficacy, Interest, Intentions, and Achievement: A Social Cognitive Perspective

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Abstract

Drawing on social cognitive perspectives, the present study examined an integrative model of the interplay among math self-efficacy, interests, aspirations, and achievement among early and middle adolescents. Based on short-term longitudinal data from approximately 400 students, analyses using fully latent structural equation analyses, establishing requisite levels of longitudinal invariance, revealed that (a) math self-efficacy positively predicted math achievement using both class grades and standardized test score operationalizations; (b) prior math achievement positively predicted basal levels of math self-efficacy but not changes in self-efficacy; (c) math interest and intentions were reciprocally linked over time; and (d) prior math interest positively predicted subsequent math self-efficacy whereas the opposite was not true. Notably, all effects were observed while accounting for prior variance in outcomes as well as the effects of known covariates. The current findings contribute to understandings of the motivational processes involved in math achievement and choosing educational pathways, and suggest that multidimensional interventions may be most profitable if both achievement and selection outcomes are at stake.

Keywords: self-efficacy; math self-efficacy; math interest; math intentions; math aspirations; STEM; longitudinal;

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Australia and several other industrialized nations require a substantial science, technology, engineering, and mathematics (STEM) workforce for economic prosperity, productivity, and global competitiveness (Office of the Chief Scientist, 2013). From 2006 to 2011, STEM jobs in Australia increased at around one-and-a-half times the rate of jobs in other industries (ABS, 2014). Furthermore, about three quarters of the fastest-growing occupations in the next decade will require STEM skills and knowledge (Becker & Park, 2011). Yet, the national demand for people in STEM outweighs the supply of STEM-trained individuals (The Australian Industry Group, 2015). One reason for this is a decline in the proportion of students choosing educational pathways in advanced math (Ainley, Kos, & Nicholas, 2008; McIlveen & Perera, 2016). Set against this climate of decreasing participation in math is the related problem of math under-performance in Australia and other Western countries (e.g., United States) (Thompson, Wernert, O'Grady, & Rodrigues, 2016). Taken together, these educational issues foreshadow a potentially bleak social and economic landscape characterized by young people entering the workforce with math knowledge and skills equivalent to only a Year 7 or 8 level, which threatens their effective participation in the 21st century workforce (Thompson, 2011) and, concomitantly, major shortages of well-trained STEM professionals.

In response to these concerns, bourgeoning research—much of it predicated on social-cognitive perspectives—has been devoted to identifying the factors implicated in achievement and educational intentions in math and related domains (Guo, Parker, Marsh, & Morin, 2015; Navarro, Flores, & Worthington, 2007; Jansen, Scherer, & Schroeders, 2015; Pajares & Graham, 1999; Lee, Lee, & Bong, 2014; Wang, 2013; Watt et al., 2012; Williams & Williams, 2010).

This literature shows that math self-efficacy is a robust social-cognitive predictor of math achievement. In addition, this literature attests to the importance of students' math interests to their intentions to pursue math-related educational pathways (Navarro et al., 2007; Waller, 2006). However, comparatively little research has examined the interplay among math efficacy, interests, intentions, and achievement using longitudinal data that allow for control of prior variance in outcomes. Examining the interplay among these constructs may yield important insights into how cognitive and affective motivational constructs operate together to influence math-related educational intentions and achievement. Drawing on social-cognitive perspectives, we test short-term longitudinal relations among math self-efficacy beliefs, interest, intentions, and achievement based on data obtained from 400 early and middle adolescents. We test models with both class-grade-and-standardized-test-score operationalizations of achievement, while also accounting for covariates. We do so using a general structural equation modeling (GSEM) framework that corrects for errors in the measurement of hypothetical constructs and allows for critical tests of longitudinal invariance.

Theoretical Background

Theories of motivation, based on the social cognitive perspective, are increasingly used to explain educational interests, intentions, and performance. A major framework in this social cognitive tradition is the social cognitive career theory (SCCT; Lent, Brown, & Hackett, 1994). The SCCT seeks to explain the related processes of developing and elaborating educational and career-related interests, forming educational and career-related intentions, selecting from academic and career choice options, and performance in educational and career domains. The SCCT holds that self-efficacy, interests, and intentions are important building blocks in the self-regulation of academic behavior (Lent, Brown, & Hackett, 2002). In the domain of math, self-efficacy denotes students' judgments about their capabilities to perform specific math-related tasks. Math interest is a cognitive-affective construct denoting positive affective experiences with, and arousal of attention toward, math-related activities (Lee et al., 2014). Here we focus on students' individual interests in math, reflecting more enduring preferences for specific stimuli characterized by re-engagement with the stimuli over time (Hidi & Renninger, 2006). Finally, math intentions refer to learners' intentions and aspirations to pursue math-related activities.

The SCCT advances several propositions about the interlinkages among efficacy, interests, intentions, and achievement. The model posits that interests and intentions develop, in part, from domain-specific self-efficacy beliefs (Lent et al., 1994). Specifically, students who believe that they are capable of performing given math tasks at required levels are more likely to develop enduring math interests and intend to pursue math-related activities. These efficacy beliefs are themselves influenced by students' interpretation of information from prior achievement-related experiences, vicarious learning experiences, verbal, and physiological and affective experiences (Lopez, Lent, Brown, & Gore, 1997) as well as individual characteristics (e.g., gender, ethnicity, and socio-economic status). Additionally, from the SCCT perspective, as individuals develop an interest for a specific domain, they form intentions to sustain or perhaps even increase their involvement in the specific domain (Lent et al., 1994). The SCCT also holds that domain-specific self-efficacy beliefs directly contribute to domain performance (Lent et al., 2002). Although there has been some support for the SCCT in math and related STEM domains in middle and high school students (Fouad & Smith, 1996; Lopez et al., 1997; Navarro et al., 2007), an important limitation of inferences drawn from this literature is that they are largely based on cross-sectional data notwithstanding the directional effects posited in the SCCT. Furthermore, little research has simulatenaouly examined math self-efficacy, interests, intentions, and achievement. Longitudinal studies, which account for prior variance in outcomes, and integrative models would allow for stronger and more integrative tests of the directional relations among math self-efficacy, interests, intentions, and achievement.

Relations Among Math Self-Efficacy, Interests, Intentions, and Achievement

Self-efficacy and interest. According to the SCCT, students' interests are influenced by their self-efficacy beliefs (Lent et al., 1994). From this perspective, students may develop interests in math activities if they believe that they can perform well in these tasks whereas they may be expected to be disinterested should they perceive themselves as incompetent in performing these tasks (Lent, Larkin, & Brown, 1989). Consistent with these views, previous research has shown that self-efficacy in math is moderately and positively associated with math-related interests (Fouad & Smith, 1999; Lent, Lopez, & Bieschke, 1991; Lopez et al., 1997; Navarro et al., 2007). However, a limitation of this work is the general reliance on cross-sectional data, prohibiting investigations of whether math self-efficacy predicts *changes* in math interests. One exception is Lent et al's (2008) longitudinal investigation demonstrating that academic engineering self-efficacy exerted a small, positive predictive effect on subsequent interests in engineering-related activities in college engineering majors.

Although the dominant self-efficacy-interest relation posited in the SCCT is the directional pathway from the former to the latter, the framework suggests that reciprocal relations may develop between the constructs (Lent et al., 1994). As such, prior interests may also influence later self-efficacy beliefs. Interests may enhance opportunities for meaningful reengagement with content towards mastery experience, leading to the development of self-efficacy beliefs (Lent et al., 2002). Furthermore, per social cognitive theory, affective states may be an important source of self-efficacy beliefs (Bandura, 1997). During task completion, individuals may interpret their (positive) affective experiences as indicators of their perceived competence (Usher & Pajares, 2009). For instance, in completing a math task, an interested student, who experiences high pleasantness, may interpret this affective experience as an indication of their task competence.

These theoretical perspectives are suggestive of a link between prior interests and subsequent self-efficacy; however, research findings have been inconsistent in the literature. For instance, Lent, Brown, Grover, and Nijer (1996) found that interest was a source of math self-efficacy for college students. Contrariwise, Lent et al. (2008) found that initial levels of interests in engineering did not significantly predict subsequent academic engineering self-efficacy. Furthermore, Ganley and Lubienski (2016) found that, though math interest at third grade did not predict math confidence at grade five, math interest at grade five significantly predicted math confidence at grade eight, though the effect was only small. For older students, whose self-competence beliefs are more likely to match their performance levels (Wigfield & Wagner, 2005), it may be that concomitant domain-specific interests, leading to greater opportunities for skill development, is more important in the development of self-efficacy beliefs.[1]

Self-efficacy and intentions. SCCT posits a direct link from self-efficacy to educational intentions. This link reflects the view that as learners feel more efficaciousness for a particular activity, they develop intentions for sustaining and even increasing engagement with the activity (Bandura, Barbaranelli, Caprara, & Pastorelli, 2001; Lent et al., 2002). Evidence shows that stronger academic self-efficacy beliefs are related to greater educational intentions and aspirations (Bandura et al., 2001; Rottinghaus, Lindley, Green, & Borgen, 2002). In math and related domains, extant evidence, largely based on cross-sectional data, supports this relation

[1] It should be noted that the measure of confidence used in Ganley and Lubienski (2016) largely comprised items tapping self-concept rather than self-efficacy beliefs per se.

(Byars-Winston et al., 2010; Cupani, de Minzi, Pérez, & Pautassi, 2010; Garriott, Flores, & Martens, 2013; Navarro et al., 2007). Although these findings are consistent with the SCCT, their reliance on single-wave data preclude inferences of directionality and change in intentions. In the present study, we examine the longitudinal relations between math self-efficacy and intentions, allowing for control of prior levels of intentions.

Even though the SCCT posits a directional link from self-efficacy to intentions, the relation between the constructs may be bidirectional. From a theoretical standpoint, intentions to pursue domain-specific activities may generate opportunities for meaningful reengagement with content and potentially repeated task-successes, which are integral to self-appraisals of task competence (Bandura, 1997; Lent et al., 2002). For instance, in the math domain, intentions to pursue further math-related coursework leads to greater math skills development as the learner encounters opportunities for mastery experiences, which should strengthen their self-efficacy beliefs. However, limited research has investigated the link from prior intentions to self-efficacy beliefs. Amongst the small amount of work, Lent et al. (2008) and Lent et al. (2010) showed that prior intentions to pursue and persist in engineering work did not predict changes in later self-efficacy beliefs in engineering for traditional and non-traditional college students, respectively. Given the conflict between theoretical perspectives and the available evidence, we leave as a research question whether prior math intentions influence subsequent math self-efficacy beliefs. Accordingly, we test alternative models in which the pathway from prior math intentions to later math self-efficacy is freely estimated versus fixed to zero.

Self-efficacy and achievement. The SCCT posits a direct link between academic self-efficacy beliefs and domain-related performance. However, from this theoretical perspective, the link is not unidirectional. Instead, the SCCT postulates reciprocal determinism of self-efficacy and achievement, such that self-efficacy and achievement are mutually reinforcing. The directional relation from self-efficacy to achievement is well-established (Pajares & Graham, 1999; Valentine, DuBois, & Cooper, 2004). This relation reflects the "self-enhancement" view of self-beliefs in achievement domains, typically examined in the self-concept literature but also relevant to self-efficacy (Williams & Williams, 2010). This perspective holds that when domain-specific self-beliefs are robust, students achieve better academic outcomes (Usher, 2016). This may be for several reasons. Students with high levels of self-efficacy persist with difficult academic problems, possess better problem solving abilities and efficiency (Hoffman & Schraw, 2009; Pajares & Miller, 1994), set challenging educational goals (Lee et al., 2014), and tend to better self-correct in academic situations (Bandura, 2001), which may foster greater academic performance. Consistent with these views, research shows that self-efficacy is a consistent positive predictor of academic achievement (Valentine et al., 2004), including in the math domain (Pajares & Graham, 1999; Parker, Marsh, Ciarrochi, Marshall, & Abduljabbar, 2014; Williams & Williams, 2010). These positive effects generalize across class grades and standardized achievement score operationalizations of math achievement (Randhawa, Beamer, & Lundberg, 1993; Fast et al., 2010).

The effect of prior achievement on later self-efficacy beliefs is comparatively less well-established. However, the available evidence suggests positive effects of prior achievement on subsequent academic self-efficacy (Valentine et al., 2004). This is consistent with the view that academic self-efficacy beliefs are informed by experiences of success and failure (Bandura, 1997; Pajares & Schunk, 2001). Indeed, from the SCCT perspective, personal performance accomplishments or mastery experiences are viewed as the most influential source of self-efficacy (Bandura, 1986). This perspective parallels the skill-development view in the self-concept literature, whereby mastery experiences with a task, achieved via task success, enhances competence beliefs (Usher, 2016). For instance, in the math achievement domain, once students perform a math-related task, they evaluate their performance with respect to personal standards of attainment, and develop or revise judgments about their competence to perform future domain-specific tasks (Usher & Pajares, 2009). In line with this theoretical standpoint, evidence suggests that prior math performance accomplishments are related to math self-efficacy beliefs (Williams & Williams, 2010).

Interests and intentions. Although the SCCT holds that the dominant pathway linking interests with intentions is the directional pathway from the former to the latter, a reciprocal effects model, positing that interests and intentions are mutually reinforcing, may better represent the relation. Indeed, this perspective is also much more consistent with the reciprocal determinism principle that is central to social cognitive theory on which the SCCT is predicated. The pathway from interests to educational and career intentions and aspirations is well-established (Achter, Lubinski, Benbow, & Eftekhari-Sanjani, 1999; Harackiewicz, Smith, & Priniski, 2016; Hirschi, 2010; Korhonen, Tapola, Linnanmäki, & Aunio, 2016; Lent et al., 2008; Lent, Paixão, Da Silva, & Leitão, 2010; Rottinghaus et al., 2002; Watt et al., 2012;), including in math and related domains (Fouad & Smith, 1996; Navarro et al., 2007; Stevens, Wang, Olivárez Jr, & Hamman, 2007; Watt, 2006; Waller, 2006; Webb, Lubinski, & Benbow, 2002). The finding that math interest predicts later math-related educational and career intentions is in line with the social cognitive view that interests are an important determinant of educational intentions (Lent et al., 1004). Indeed, intentions reflect a cognitive-motivational expression of a learner's primary choice goal from among specific interests (Lent et al., 2002; Silvia, 2001). Specifically, for math learners, the experience of interest during a math task, characterized by feelings of enjoyment and increased attention during the task (Hidi & Renninger, 2006), may guide and direct students' movement towards math-related activities and environments through their intentions to pursue and persist with such activities.

Hitherto, the scientific literature has been primarily preoccupied with examining the directional pathway from interests to intentions and aspirations. However, prior intentions may be equally important in fostering the development of later interests. Interest theory holds that repeated exposure to environments that support the pursuit of interests is integral to the development of interest from a situation-dependent cognitive-affective state to a more stable and generalizable preference for certain activities (Harackiewicz et al., 2016; Renninger & Hidi, 2016). Prior intentions or aspirations to pursue certain activities, which have themselves been shown to be informed by interests (Hirschi, 2010), may facilitate the selection of environments that foster the development of these interests. This is because intentions organize and guide behavior and help to sustain behavior over time (Harackiewicz et al., 2008; Lent et al., 1994). Notwithstanding the intuitiveness of this link, and its consistency with social cognitive theory, little research has been devoted to examining the association. A notable exception is Hirschi's (2010) investigation of reciprocal relations among interests and intentions, which found that secondary school students' prior vocational intentions and aspirations predicted vocational interests one year later. However, in this study, intentions and interests were relatively domain general. In the present study, we examine the reciprocal pathways linking math intentions and interests.

Interests and achievement. The conventional wisdom about the role of interest in the educative process is that interest increases learning. Indeed, interest theory posits that the experience of interests can promote achievement by increasing engagement and attention

(Harackiewicz et al., 2016). For interested students, increased attentional resources devoted to the academic object and pleasant affect during task engagement may enhance the learning process. Interested students have been shown to exert greater academic effort (Trautwein et al., 2015), adopt mastery goals (Harackiewicz et al., 2008), and better self-regulate their learning (Lee et al., 2014; McWhaw & Abrami, 2001), which may all contribute to superior performance (Lee et al., 2014; Trautwein, Lüdtke, Roberts, Schnyder, & Niggli, 2009). Despite this theoretical position, empirical findings on the influence of interest on achievement are mixed. Although studies have reported positive links from interest to achievement (Schiefele, Krapp, & Winteler, 1992), including in the math domain based on both cross sectional (Jansen, Lüdtke, & Schroeders, 2016; Lee et al., 2014) and longitudinal (Köller, Baumert, & Schnabel, 2001) data, other studies have found near-zero (Ganley & Lubienski, 2016; Marsh, Taruwein, Lüdtke, Köller, & Baumert, 2005) or even negative links (Liu, 2009; Pinxten, Marsh, De Fraine, Van Den Noorgate, & Van Damme, 2014), particularly when accounting for competence beliefs (Marsh et al., 2005). One reason for the null and negative effects may be that competence beliefs and interests have shared pathways to achievement through comparable motivational and self-regulative mechanisms. Once the effects of competence beliefs are controlled, the remaining effect of interests may reflect the motivation to broaden exploration of certain objects (Fredrickson, 1998), which, while important to future intentions and decisions to engage with the domain (Blustein, 1989), may be immediately deleterious to task completion (Pinxten et al., 2014; Sansone, Thoman, & Fraughton, 2015). In the present study, given the inclusion of math self-efficacy, we expect the link from interest to achievement to be null or negative (Ganley & Lubienski, 2016). This prediction should be set against the expectation for a positive effect of interest on intentions to pursue math.

The role of prior achievement in shaping subsequent interest has not been widely-investigated. Even from the perspective of general interest theory (Hidi & Renninger, 2016), there has been limited elaboration of the potential effects of prior achievement on interests. From the SCCT perspective, interests are believed to be formed through relevant learning experiences, including performance accomplishments, and the self-efficacy beliefs and expectations that they promote (Lent et al., 1994). The little empirical work that exists suggests that prior achievement may have a small effect on subsequent interests (Ganley & Lubienski, 2016; Pinxten et al., 2014). For instance, Ganley and Lubienski (2016) found that math achievement in the third and fifth grades was related to small changes in fifth and eighth grade math interest, respectively, in US students. Furthermore, Pinxten et al. (2014) found that prior achievement in math predicted basal levels of Grade 4 Flemish students' math enjoyment, reflecting, at least in part, math interest. However, the positive effects of prior math achievement on subsequent changes in math enjoyment were only modest and reduced to zero by the time students reached seventh grade. The experience of academic attainment may serve as a mastery learning experience that provides an experiential source for the initial development and refinement of interests. Based on theory and prior evidence, we expect that prior math achievement will positively predict basal levels of math interests as in Pinxten et al., and that effects on subsequent changes in interests will be comparatively smaller. Indeed, it is unlikely that single experience of academic success, reflected in previous term grades, will have strong effects on changes in interest levels over basal levels, particularly over a short-period of time. Instead, cumulative learning experiences, involving not only performance accomplishments but also vicarious learning experiences and verbal and social persuasion, are perhaps more likely to influence subsequent changes in interests over an extended period.

Intentions and achievement. Research shows that prior math achievement is associated with greater intentions to pursue math-related educational and career pathways. For instance, Wang (2013) found that standardized math test scores in high school predicted intentions to pursue a postsecondary STEM field of study in approximately 6,000 students. Furthermore, Wang (2012) reported that students' 10th grade math performance predicted 12th grade aspirations to pursue math-related careers among about 3,000 adolescents. From the SCCT perspective, high prior achievement may serve as a positive learning experience that sustains or even increases intentions to pursue certain educational and career pathways. However, the empirical research has not examined whether prior math achievement predicts changes in math intentions over and above initial levels, which would constitute stronger evidence for a directional relation.

Prior intentions may also be related to achievement. From the SCCT perspective, intentions for activity involvement may foster performance experiences through learners' choice behaviors (Lent et al., 2002). For instance, an individual may intend to pursue a math education or career path, leading to goal-related actions, such as enrolling in a further math classes, which results in particular performance experiences. Alternatively, intentions to pursue a certain level of education (e.g., advanced math track) may necessitate superior attainments to reach that level of education (Abu-Hilal, 2000). In this case, domain-specific attainments depend, at least in part, on intentions. There is some evidence for a link from intentions to achievement (Abu-Hilal, 2000; Meece, Wigfield, & Eccles, 1990; Walkey, McClure, Meyer, & Weir, 2013). For example, Abu-Hilal (2000) and Walkey et al. (2013) found that intentions to pursue further education positively predicted achievement in high school students. However, these studies did not investigate the effects of intentions on changes in achievement beyond basal levels. Give the absence of robust evidence for a link from intentions to achievement, we propose as a research question whether prior math intentions predict changes in math achievement beyond prior achievement.

Effects of gender and grade level. From the SCCT perspective (Lent et al., 1994), gendered socialization experiences impact students' motivational beliefs and achievement. Although there is increasing evidence showing comparable math achievement for males and females (Else-Quest, Hyde, & Linn, 2010), gender effects on math grades may differ as a function of the type of achievement index (viz., class grades versus standardized achievement). Males have been shown to outperform females on standard achievement tests whereas the opposite is true for class grades (Duckworth & Seligman, 2006). This difference has been attributed to several mechanisms, including greater stereotype threat among women (Steele, 1997), performance differences by item format (Lindberg, Hyde, & Petersen, 2010), and differences in self-discipline (Duckworth & Seligman, 2006). Nevertheless, effect sizes for gender differences in math achievement tend to be small (Else-Quest et al., 2010; Lindberg et al., 2010). Larger gender differences have been found in motivational constructs. Females students have been shown to have lower math self-efficacy (Else-Quest et al., 2010) and math-related intentions and aspirations than females (Riegle-Crumb, Moore, & Ramos-Wada, 2011; Watt, 2006). Evidence also shows that females report lower math interest than males (Guo et al., 2015; Preckel, Goetz, Pekrun, & Kleine, 2008). However, studies do not routinely control for the concomitant effects of math self-efficacy beliefs in the gender-interest relations, which may obscure findings. Indeed, it may be that, after partialling out the effects of beliefs about competence to perform specific math tasks, females report comparable levels of math interest. We account for the effects of gender on the substantive constructs in the present study.

Grade-level differences are also important to consider in models of motivational processes in math. There is evidence that math interests decrease from later primary school into high school and plateaus around grade eight to nine (Frenzel, Goetz, Pekrun, & Watt, 2010). Furthermore, there is evidence that math-related competence beliefs decrease as a function of increasing grade level (Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002). Given these findings, and the observation that the standardized achievement test scores used in the present study are grade-dependent[2], the grade-level heterogeneity in the present sample necessitates adequate statistical control.

The Present Study

Drawing on social-cognitive perspectives (Lent et al., 1994), the present study aims to examine a model of the interplay among math self-efficacy beliefs, interests, intentions, and achievement in early and middle adolescents. The conceptual model examined is shown in Figure 1. The relations are tested using data from 400 school students. In doing so, we aim to fill a gap in the literature on the motivational pathways to educational intentions and achievement. Specifically, we examine whether the links among math self-efficacy, interests, intentions, and achievement are reciprocal or unidirectional. To the authors' knowledge, no studies have simultaneously investigated the longitudinal relations of math self-efficacy, interests, intentions, and achievement. Furthermore, we examine these relations with both class grades and standardized achievement test operationalizations of math achievement. Based on theory and the evidence reviewed, our main research hypotheses and questions follow:

[2] Standardized achievement in the present study is operationalized using Australian NAPLAN numeracy test scores. Across grade levels, NAPLAN numeracy scores are reported on a common scale rather than a separate scale for each grade level. This means that NAPLAN numeracy scores increase systematically as a function of increasing grade level, reflecting increasing proficiency as a student progresses through the curriculum.

Hypothesis 1 (H1): Math self-efficacy is expected to be a modest, positive predictor of subsequent math interests, controlling for initial levels of interest.

Hypothesis 2 (H2): Prior math interest will be a small, positive predictor of subsequent math self-efficacy, accounting for initial levels of self-efficacy.

Hypothesis 3 (H3): Math self-efficacy is expected to be a small, positive predictor of changes in math intention beyond basal levels.

Research Question 1 (RQ #2): Do prior math intentions influence future math self-efficacy beliefs beyond initial levels of efficacy? To examine this research question, we test a model in which the path from prior intention to later math self-efficacy is freely estimated against a model in which the path is fixed to zero.

Hypothesis 4 (H4): Math self-efficacy is hypothesized to moderately and positively predict math achievement over and above prior math achievement.

Hypothesis 5 (H5): Prior math achievement is expected to positively predict initial levels of math self-efficacy beliefs and effects on short-term changes in self-efficacy will be comparatively smaller.

Hypothesis 6 (H6): Math interest is expected to positively predict math-related intentions, accounting for prior levels of intentions.

Hypothesis 7 (H7): Prior math intentions will positively predict subsequent interests, controlling for initial levels of interests.

Hypothesis 8 (H8): We expect that, accounting for the effects of math self-efficacy beliefs, math interest will not be significantly related to math achievement. To examine this hypothesis, we test an alternative model in which the path from prior interests to subsequent achievement is freely estimated against a model in which the path is fixed to zero.

Hypothesis 9 (H9): Prior math achievement is expected to positively predict basal level of math interests and, to a lesser extent, short-term changes in math interest.

Hypothesis 10 (H10): Prior math achievement is expected to positively predict math intentions initially, and to a lesser extent, changes in math intentions.

Research Question 2 (RQ #2). Do prior math intentions influence subsequent math performance? To examine this research question, we test a model in which the path from prior intention to math performance is freely estimated against a model in which the path is fixed to zero.

We examine these research hypotheses and questions while accounting for the effects of grade level and gender. Figure 1 shows a schematic of the model(s) to be tested.

Figure 1 about here

Method

Participants and Procedure

Participants were 400 school students enrolled in two independent (i.e., non-government) schools in Eastern Australia. Approximately 69% (n = 275) of the participants were female, and the mean age of participants was 13.14 (SD = 1.27). Year level ranged from Grade 6 through Grade 10, with 8.5% (n = 34) of participants in Grade 6, 28.3% (n = 113) in Grade 7, 23.3% (n = 93) in Grade 8, 16.3% in Grade 9 (n = 65), and 23.8% (n = 95) in Grade 10. All participants were enrolled in mandatory mathematics classes per Australian curriculum requirements.

Participants completed a battery of questionnaires via computerized administration under teacher supervision during class time at two time points during the academic year, separated by a six-month interval (Time 1 [T1] = Beginning of Semester One 2016; Time 2 [T2] = End of Semester One 2016). The initial battery of questionnaires contained socio-demographic items as well as measures of math self-efficacy, interests, and intentions. The follow-up battery contained only measures of the substantive constructs. Teachers explained the purpose of the research and the rating scales to students, and instructed students to complete the instruments on their own. In addition to these measures, the researchers retrieved data on students' Semester One cumulative math class grades, prior math class grades (viz., Semester 2 2015 grades), and most recent national standardized achievement test scores. Ethics approval was granted by the Institutional Review Board, and parental consent and student assent were granted for all participating students. Students were advised at both survey administrations that the research is entirely voluntary, and that they could leave the study at their own will or with parent authorization.

Measures

Math self-efficacy. Math self-efficacy was measured using the Math-Self-Efficacy scale from the Education Longitudinal Study of 2002 (ELS: 2002). This measure comprises five items designed to measure students' perceived capabilities to perform specific math-related tasks, such as successfully complete math tests and understand difficult math material in textbooks. Items are rated on a four-point Likert-type scale ranging from 1 (*Almost Never*) to 4 (*Always*). A sample item is "I'm confident I can do an excellent job on my math assignments". Scores generated from the measure have been shown to be reliable, and validity evidence has also been obtained (NCES, 2003). In the present sample, model-based composite reliabilities[3] and

[3] This coefficient is McDonald's (1970) Omega coefficient of composite reliability given as $\omega = (\Sigma|\lambda_i|)^2 / (\Sigma|\lambda_i|)^2 + \Sigma\delta_{ii})$, where λ_i are the factor loadings and δ_{ii} are the residual variances obtained from a common factor model analysis. The Omega coefficient should be preferred to the Cronbach's alpha coefficient as its accounts for the strength of the association of each item with its corresponding latent factor as well as controls for item errors of measurement (Sijtsma, 2009). Nevertheless, we also report coefficient alpha in keeping with tradition.

coefficient alpha reliabilities at both T1 (ω = .911; α = .890) and T2 (ω = .939; α = .911) were acceptable.

Math interest. Math interest was measured using the PISA 2003 index of math interest (Organisation for Economic Cooperation and Development, 2005). This index comprises four items, rated on a four-point scale, ranging from 1 (*Strongly Disagree*) to 4 (*Strongly Agree*), designed to measure cognitive-affective aspects of math interests. A sample item from the measure is "I am interested in the things I learn in mathematics". Scores from this measure have been shown to be reliable and validity evidence has been obtained (OECD, 2005). For the present sample, model-based composite reliabilities and coefficient alpha reliabilities at both T1 (ω = .911; α = .935) and T2 (ω = .939; α = .955) were acceptable.

Math intentions. Math intentions were measured using three items from the Math and Science Goal Intentions Scale (Smith & Fouad, 1999). This seven-item measure, rated on a six-point Likert-type scale, ranging from 1 (*Very strongly disagree*) to 6 (*Very strongly agree*), is designed to measure learners' intentions to pursue math and science-related academic courses and careers. In the present study, only the three items grounded in the math domain were used. A sample item is "I plan to take more math classes in school than will be required of me". Scores from the instrument have been shown to be reliable and valid (Smith & Fouad, 1999). In the present sample, model-based composite reliabilities and coefficient alpha reliabilities at both T1 (ω = .743; α = .690) and T2 (ω = .799; α = .755) were acceptable. Note that coefficient alpha is, in part, a function of scale length. Although the internal consistency estimates of the math intentions scores are somewhat low at both time points, applying the Spearman-Brown prophecy formula to the existing estimates and scale length, the reliability estimates would be .788 and .837, respectively, with an increase of even 2 items. For this reason, the reliabilities reported herein are reasonable with respect to scale length. Nevertheless, the present study uses latent variable models that control for measurement error.

Math achievement. Two distinct operationalizations of math achievement were used in this study. First, Semester 1 2016 class grades were used to index achievement. Class grades lie on a 15-point scale, indexing students' cumulative math performance for the semester based on results of individual exams and assignments. The grades reflect achievement in three areas of math competence as follows: (a) knowledge and procedure; (b) modeling and problem solving; and (c) communication and justification. These three criteria are assessed on all assessment pieces and equally weighted. Second, standardized math achievement was operationalized by students' numeracy scores in the National Assessment Program in Literacy and Numeracy (NAPLAN). NAPLAN is a nationally standardized assessment of literacy and numeracy administered by the Australian Curriculum and Assessment and Reporting Authority (ACARA). We transformed the observed NAPLAN numeracy scores (hereafter standardized achievement) by dividing by a factor of 10 to reduce the observed variance as it was too divergent from the variances of the remaining manifest variables, which may yield model convergence problems. Finally, prior math achievement, operationalized as students' Semester 2 2015 class grades, which also lies on a 15-point scale, was also included in the model.

Covariates. Gender (0 = male, 1 = female) was included in the statistical models as an observed covariate. Furthermore, given that grade level differed across participants and has been shown to be implicated in various motivational constructs and academic outcomes, we included grade as a covariate in the hypothesized models.

Statistical Analyses

Analyses were conducted in a general latent variable modeling framework. Initially, longitudinal measurement invariance models were tested to examine the statistical equivalence of the scale item scores across the two time points. Tests of cross-time invariance are an important pre-requisite to examining construct relations over time. Unless each construct is measured in an equivalent way over time, and the observed manifestations are also operating equivalently across time, the interpretation of lagged relation coefficients (as well as mean stability coefficients) is potentially confounded (Widaman, Ferrer, & Conger, 2010). These longitudinal tests were conducted in line with a novel taxonomy of longitudinal invariance tests with ordered categorical data (Liu et al., 2016; Perera, McIlveen, Burton, & Corser, 2015). Initially, in the least restrictive configurally invariant model, with no cross-time invariance restrictions, math self-efficacy, math interest, and math intentions at both time points were specified as independent clusters CFA factors indexed by their respective T1 and T2 items. From this baseline model, increasingly restrictive cross-time equality constraints were additively imposed on the factor loadings (i.e., loading invariance model), item thresholds[4] (threshold invariance model), and item uniquenesses (unique factor invariance model). Across the invariance models, the substantive factors were permitted to freely covary with each other. In addition, the observed covariates and outcomes (i.e., gender, grade level, prior achievement, class grades/standardized achievement) were included as manifest variables in these invariance models with freely estimated covariances with all substantive factors as well among the observed covariates themselves (Little, Preacher, Selig, & Card, 2007). It should be noted that two distinct

[4] When ordinal data are examined, both item thresholds and intercepts are not simultaneously identified. Item thresholds refer to points on the unobserved response variate underlying the observed ordinal item at which observed scores, on average, change from one response category to another. For every k response category constituting a response scale, there are k – 1 thresholds dividing the latent response variate distribution. Contrariwise, item intercepts refer to the intercept of the link between the latent factor and latent response variate. The default in Mplus is the modeling of item thresholds as reported herein (Perera, Izadikhah, O'Connor, & McIlveen, 2016).

sets of invariance models were tested. One set included class grades as the math achievement index; the other set included standardized achievement as the achievement index.

In longitudinal analyses, in which there are repeated measurements of construct indicators, including a priori cross-wave correlated uniquenesses is crucial (Marsh & Hau, 1996). This is because administering the same item across multiple time points likely generates systematic covariance between items over and above the substantive factors. The omission of these cross-wave correlated uniquenesses may lead to upwardly biased stability coefficients linking corresponding factor across time (Jöreskog, 1979). Accordingly, for the analytic models examined, we specified sets of 12 correlated uniquenesses to account for the residual covariance between corresponding items administered at T1 and T2.

In addition to these cross-time correlated uniquenesses, we also specified two-sets of a priori within-construct (viz., math self-efficacy) and within-wave correlated uniquenesses to account for construct-irrelevant multidimensionality due to item-wording effects (Perera et al., 2016). Although the longitudinal common factor model typically assumes that the unique factor covariances are zero, if there is a strong a priori rationale for the incorporation of these parameters due to construct-irrelevant multidimensionality, the failure to incorporate these correlated residual terms can upwardly bias estimates of (a) factor loadings where the unique factors are within-construct and (b) factor correlations where the unique factors are between-constructs. In the present study, covariances between the uniqueness terms for (a) Item 1 and Item 4 and (b) Item 2 and Item 3 of the Math Self-Efficacy Scale over both time points were specified due to highly similar item wordings (Item 1: “I'm confident that I can do an excellent job on my math tests”, Item 4: “I’m confident I can do an excellent job on my math assignments”; Item 2: “I’m certain I can understand the most difficult material presented in math texts", Item 3: "I'm confident I can understand the most difficult material presented by my math teacher"). Consistent with Liu et al's (2016) recommendations, the corresponding within-wave correlated uniquenesses were constrained to equality over the time.

Subject to support for at least loading invariance, we reparameterized the final longitudinal invariance model to reflect our expectations for structural relations among the constructs. We examined four distinct structural models. In the first model (SM #1)[5], all autoregressive and cross-lagged paths among latent math self-efficacy, interest, intentions, prior achievement, and class-grades/standardized achievement were specified. In addition, covariances among the T1 constructs were freely estimated. For the covariates, paths from gender and grade level to the T1 and T2 math self-efficacy, interest, and intentions constructs were freely estimated. Paths from prior achievement to the T1 and T2 latent constructs were also specified. Covariances of gender and grade level with prior achievement were freely estimated. In a second model (SM #2), the path from T1 math intentions to T2 self-efficacy beliefs was fixed to zero to examine RQ #1. A third model (SM #3) specified the path from T1 interests to semester-end class grades as fixed to zero. Finally, in a fourth structural model (SM #4), the path from prior intentions to subsequent math achievement was fixed to zero to test RQ #3. These structural specifications result in a fully saturated model for SM #1, and one more degree of freedom for SM #2, SM #3, and SM #4. We comparatively test these structural models. As with the longitudinal measurement invariance tests, we specified and tested to two sets of structural models—one with class grades as the outcome, and the other with standardized achievement as the outcome.

[5] SM #1 – SM #4 are used as designations for the alternative structural models. The lowercase "a" and "b" are used to designate class grades and standardized achievement models, respectively. For instance, SM #2a refers to the second structural model with class grades whereas SM #4b refers to the fourth structural model with standardized achievement.

Analyses were performed using Mplus 8.0 (Muthén & Muthén, 1998-2017). Solutions were estimated using the diagonal weighted least squares estimator with a mean and variance adjustment to the test statistic and robust standard errors, operationalized as the WLSMV estimator in Mplus. This estimation routine is more suitable for ordered-categorical response items, particularly those with finite response categories, than the more familiar maximum likelihood estimator assuming a linear factor model. For the present estimation, we chose Theta parameterization as unique variances are model parameters under this parameterization and can thus have equality constraints directly imposed. All models were estimated while accounting for students' nesting within classroom using the design-based correction of standard errors, operationalized via the complex design option in Mplus (Muthén & Muthén, 1998-2017). For model fit evaluation, an inclusive approach was used, involving a consideration of fit indices and the theoretical consistency and admissibility of parameter estimates. As the χ^2 can be oversensitive to minor model misspecifications given even moderate-sized samples and contains a restrictive hypothesis test (i.e., exact fit), three approximate fit indices were used: Root Mean Square Error of Approximation (RMSEA), ≤ .050 and .080 for close and reasonable fit, respectively; Comparative Fit Index (CFI) and Tucker-Lewis Index, ≥ .900 and .950 for acceptable and excellent fit, respectively. For nested model comparisons, because the adjusted χ^2 difference (MD $\Delta\chi^2$) test appropriate for the WLSMV estimator also tends to be sensitive to even trivial differences, changes in the CFI (ΔCFI) and RMSEA (ΔRMSEA) were primarily used. A decrease in the CFI and increase in the RMSEA of less than .010 and .015, respectively, are indicative of support for a more restrictive model (Chen, 2007; Cheung & Rensvold, 2002).

As is common in even short-term longitudinal studies, there were missing data across the observed variables. Missingness was largely due to attrition rather than within-wave nonresponse, with the exception of the achievement variables. For the manifest indicators of the latent constructs, the amount of within-wave missingness was small, ranging from 0.00% to 0.80% (M = 0.47%) at T1 and 0.00% to 1.00% (M = 0.17%) at T2. For the achievement outcomes, there was comparatively more missingness, with 17.5% missingness on standardized achievement and 3.3% of missingness on class grades. This missingness was largely due to absences on the day of standardized achievement testing, pending standardized achievement results, and teacher delays in processing class grades for some students. Contrary to the within-wave missingness, there was a larger amount of across-wave missing data. Approximately, 50% of the sample completed the follow-up measures of math self-efficacy, interests, and intentions. Attrition often leads to data that are not missing completely at random (MCAR). In multi-wave studies with missingness due to attrition, MCAR assumes that participant dropout is independent of responses at other occasions, which is rather restrictive.

The chief concern with missing data due to attrition is selectivity effects where individuals with specific characteristics are more likely to be retained in the study. Thus, we compared participants with both waves of data against those with only T1 data on the math self-efficacy, interests, and intentions variables as well as the achievement outcomes and gender and grade level. Completes and non-completers did not significantly differ on math self-efficacy, t (394) = -0.481, p > .05, interest, t (396) = 0.079, p > .05, or intentions, t (394) = .161, p > .05. However, completers and non-completers did significantly differ on class grades, t (385) = 2.376, p < .05, d = 0.242 and standardized achievement, t (328) = 2.257, p < .05, d = 0.248, though the differences were relatively weak. In addition, completers and non-completers were found to significantly differ on gender, χ^2 (1) = 41.370, p < .001, ϕ = -0.322, and grade level, χ^2 (4) = 80.769, p < .001, V =.449. Accordingly, to handle the missing data, we allowed missingness to be a function of gender, grade level, and prior achievement. Inclusion of these variables strengthens the plausibility that the missing data are missing systematically as a function of the covariates. This is the case because both gender and grade level were covariate predictor of missingness. Furthermore, as class-grades and standardized achievement were also significantly related to missingness, the inclusion of prior achievement data as a covariate provides some protection against the violation of the missing at random assumption. Assuming only covariate variables have an effect on the missingness (i.e., the so-called "MARX" condition), weighted least squares estimators yield consistent estimates (Asparouhov & Muthén, 2010).

Results

Longitudinal Factorial Invariance

Descriptive statistics and correlations for the manifest variables are shown in Supplemental Appendix A. Table 1 shows the test statistics and fit indices for two sets of longitudinal invariance models. For the models including class-grades, the configural invariance model provided a very good fit to the data, indicating that the same general pattern of loadings holds across time. Additionally, support was found for the invariance of the factor loadings. We also found support for the invariance of the item-thresholds, which implies that, holding constant levels of the latent factors, the threshold level of moving from one response category to the next is equivalent over time for the present items. Finally, support was obtained for the equivalence of the item uniquenesses. For the models including standardized achievement, a comparable pattern of results was observed. The baseline model provided a very good fit to the data. In addition, support was found for the invariance of the factor loadings, item thresholds, and uniquenesses.

Estimates of the factor loadings from the final models of full longitudinal measurement invariance are shown in Table 2.

Table 1 about here

Table 2 about here

Structural Models

Model with class-grades. We reparameterized the final model of full longitudinal measurement invariance, namely the unrestricted factor variance-covariance matrix, to specify the substantive structural relationships. Results of the tests of the structural model are reported in Table 3. The test of SM #1a—a fully-forward saturated model—resulted in identical fit (within rounding error of the likelihood ratio test statistic) to the final model of strict longitudinal invariance. This model was compared against the more restrictive SM #2a, with the path from T1 math intentions to T2 math self-efficacy fixed to zero. The test of SM #2a resulted in an excellent fit to the data in absolute terms, and, notably, no significant decrement in fit relative to SM #2a. Next, we tested SM#2a against SM#3a, with the path from prior math interest to semester-end grades fixed to zero. SM #3a provided an excellent fit to the data, and no significant degradation in fit relative to SM #2a. Finally, we tested SM #3a against SM #4a, with T1 math intentions to math achievement additionally fixed to zero. SM #4a provided an excellent fit to the data, and no significant degradation in fit relative to the more complex SM #3a. Thus, SM #4a was retained for interpretation.

Table 3 about here

Table 4 shows the standardized path coefficients from the structural model with class-grades. As expected, the autoregressive paths between the latent constructs were the strongest effects observed (β = .609-.655, M = .626). The between-construct effects were only partially consistent with our predictions. Inconsistent with H1 and H3, prior math self-efficacy did not significantly predict subsequent interests or intentions. However, in line with H2, prior math interest positively and significantly predicted changes in math self-efficacy. Prior math intentions did not significantly predict subsequent math self-efficacy beliefs as a model fixing this path to zero did not result in a degradation in fit relative to a model in which the path was freely estimated. Consistent with H4, initial math self-efficacy was a significant, positive predictor of class-grades. Partially consistent with H5, prior math achievement positively predicted initial levels of math self-efficacy, but did not predict changes in self-efficacy above these basal levels. In line with H5 and H6, there were significant reciprocal relations between math interest and math intentions: initial math interest significantly predicted subsequent math intentions, and math intentions significantly and positively predicted subsequent interest. Consistent with H8, after accounting for math self-efficacy beliefs, math interest was not a significant predictor as a model fixing this path zero did not results in a significant decrement in fit relative to a model in which the path was freely estimated. Partially consistent with H9 and H10, prior math achievement positively predicted T1 math interest and math intentions, respectively, but was not significantly related to changes in interest and intentions at T2. Prior math intentions did not significantly predict semester-end class grades as a model containing this path to zero did not significantly worsen fit relative to a model in which the path was freely estimated.

For the covariate effects, gender and year level had significant, negative effects on math self-efficacy, indicating that girls and higher year levels reported significantly lower math self-efficacy than boys and lower year levels, respectively. For interests, there were negative effects of gender and year level that approached, but did not reach significance. No significant effects of gender and year level on math intentions were observed. In terms of math class-grades, females reported significantly higher achievement than males, though the effect was small.

Table 4 about here

Model with standardized achievement. As with the model for class-grades, we reparameterized the final model of longitudinal invariance with standardized achievement to specify the substantive structural relationships. Table 3 shows the results of the tests of the structural models with standardized achievement. The test of SM #1a resulted in identical fit to the model of strict longitudinal invariance, which is to be expected as SM #1a is saturated with respect to the specification of structural parameters. Support was also found, additively, for SM #2a, SM #3a, and SM #4a. Thus, the most parsimonious model—SM #4—was retained for interpretation of estimation.

Table 4 shows parameter estimates from the retained structural model with standardized achievement. Notably, the pattern of results for the present model was virtually identical (i.e., typically within rounding error) to the results obtained from the model with class-grades. The only notable difference was the significant effect of gender on standardized achievement, with females scoring significantly lower than males. It should be noted that the large effect of grade level on standardized achievement should be expected as NAPLAN numeracy scores increase systematically as a function of increasing grade level.

Discussion

The present study provides one of the more comprehensive tests of the SCCT model of the interplay among math self-efficacy beliefs, interests, intentions, and achievement based on short-term longitudinal data from school students. Notably, the results provide strong support for some of the pathways hypothesized in the SCCT using robust longitudinal latent variable models that (a) provide adequate control for prior variance, (b) establish requisite levels of longitudinal invariance in the presence of ordered categorical data, and (c) control for errors of measurement. As expected, math self-efficacy beliefs positively predicted subsequent math achievement using both class grades and standardized achievement test score operationalizations. Furthermore, students' interests in math were predictive of their math-related self-efficacy beliefs. In addition, support was obtained for reciprocal relations between students' math interest and intentions, suggesting these constructs may be mutually reinforcing in choice-related motivational processes. Although the size of the effects observed in the study were generally small to moderate, it is important to note that the coefficients index incremental effects beyond autoregressive effects and effects of other substantive constructs and covariates. Indeed, the size of the autoregressive paths in the study is suggestive of considerable stability over the six month-period, leaving only little variance to be explained and thus making the detection of additive effects difficult. These findings, as well the observations of some theoretically unexpected null results, are discussed with respect to theory and prior empirical work below.

The study findings were partially consistent with the SCCT propositions relating to the relations between math self-efficacy and achievement. In line with a wealth of prior work (Fast et al., 2010; Pajares & Graham, 1999; Parker et al., 2014; Williams & Williams, 2010), math self-efficacy was found to be a significant and positive predictor of math achievement, over and above initial levels of math achievement. Notably, math self-efficacy positively predicted changes in achievement using both standardized test score and class grade operationalizations of math achievement. The standardized effect of math self-efficacy was stronger for class grades than for standardized test scores. This pattern of findings has also been observed in prior meta-analytic work (Multon, Brown, & Lent, 1991) and may be attributed to several sources. First, the self-efficacy measure used in this study asked students about their perceived capability to (a) understand difficult math material presented in textbooks and by teachers, (b) do well on math assignments, and (c) master the skills taught in math class. The content of these self-efficacy indices corresponds much more closely with proximal class-grades-based tasks than more distal and one-off standardized achievement measures (Multon et al., 1991). Furthermore, math self-efficacy could be more strongly related to class grades because these achievement indices serve as a more enduring and salient source of feedback relevant to competence beliefs (Wylie, 1979). Finally, class grades reflect long-term performance on a series of distinct tasks (e.g., class exams, assignments, discussions) (Duckworth & Seligman, 2006), and the grading process may reflect motivational factors, such as the amount of effort invested. In contrast, standardized achievement tests are more momentary, requiring only short-term engagement and less diversity in specific tasks. Given the apparently longer-term nature of class grades, achievement is likely to require more sustained motivation and engagement that may be fostered by greater self-efficacy (Marsh et al., 2005).

Despite support for the directional pathway from math self-efficacy to achievement, the inverse effect from prior achievement to subsequent self-efficacy beliefs was only partially consistent with predictions. Specifically, prior achievement was shown to significantly predict initial levels of math self-efficacy but not changes in self-efficacy beliefs over and above these initial levels. This is somewhat inconsistent with the social cognitive view that self-efficacy beliefs are affected, at least in part, by experiences of success and failure in academic environments (Lent et al., 2002). High attainment in an achievement domain may be viewed as a mastery experience that enhances beliefs about capability. This suggests that ongoing experiences of success (or failure) in math should influence subsequent changes in math self-efficacy beliefs. One reason for the absence of an effect on changes in math self-efficacy is that objective performance indices, such as prior achievement, may not reflect the mastery experiences discussed by Bandura (1997) insofar as they reflect objective attainment rather than students' interpretations of an event (Usher & Pajares, 2009). Although prior achievement may be important for basal levels of self-efficacy, it may be students' perceived mastery experiences, involving their interpretations of an event in terms of success and failure, that influence subsequent changes in self-efficacy (Lopez, Lent, Brown, & Gore, 1997).

Prior math interests were shown to positively predict changes in math self-efficacy beliefs six months later but the opposite was not true. These findings are important insofar as they tentatively clarify prior evidence showing cross-sectional associations between math-related interests and self-efficacy. The predictive effect of interest on positive changes in math self-efficacy aligns with prior evidence showing that interests may serve as a cognitive-affective motivational source of self-efficacy beliefs (Lent et al., 1996). Specifically, from a social-cognitive standpoint (Bandura, 1997), the experience of enjoyment as part of the interest process during task engagement may be a positive affective experience that may be interpreted as an indication of one's perceived competence (Usher & Pajares, 2009). Furthermore, the experience of interest may promote repeated engagement in math-related tasks that allows for sustained math problem identification, exploration, and solving towards skill development, which may potentially enhance future self-efficacy beliefs. Direct empirical tests of this purported temporal chain of effects may be profitably conducted in future work.

The absence of a significant longitudinal pathway from math self-efficacy to interests may be somewhat surprising, particularly considering that this directional effect is viewed as the dominant pathway underlying the self-efficacy-interest association (Lent et al., 1994). From a social cognitive perspective, students may be expected to develop interests in math tasks should they believe they are capable of performing well in the tasks (Lent et al., 1989). Nevertheless, the finding aligns with some previous evidence showing that math competence beliefs are not significantly predictive of future math interests (Ganley & Lubienski, 2016). Even where longitudinal effects have been reported, these tend to be very small in magnitude (Lent et al., 2008). The findings suggest that believing that one is capable at performing domain-specific tasks may not necessarily be strongly implicated in liking the domain. Indeed, it is conceivable that individuals can be interested in a domain and its concomitant activities in spite of lacking confidence in their ability to succeed at the task (Denissen, Zarrett, & Eccles, 2007). Similarly, students who perceive themselves as capable of successfully performing tasks may not necessarily be interested in those tasks (Renninger, Ewen, & Lasher, 2002). The near null relations obtained in this and other studies support this position. Another possibility is that the pathway from math self-efficacy to math interest is grade-level dependent. Beliefs about the ability to successfully perform tasks may be more important for interests as students get older and their competence beliefs match their performance levels, and identity development becomes more intertwined with what one believes he or she is capable of doing and is good at. Future research would be well served by examining this moderation hypothesis.

An apparently novel contribution of the present study is the investigation of reciprocal relations between math self-efficacy beliefs and math intentions over the six-month time frame. Findings showed that math self-efficacy was not significantly predictive of later math intentions, and that math intentions did not significantly predict subsequent math self-efficacy. Although the absence of effects is inconsistent with cross-sectional evidence for a self-efficacy-intentions link (Byars-Winston et al., 2010; Navarro et al., 2007), the findings converge with some previous longitudinal work in the engineering domain (Lent et al., 2008, 2010). Even though students may be efficacious about specific math tasks, they may not necessarily develop aspirations to pursue math pathways, perhaps due to the absence of interests in the domain. On the other hand, one reason why prior intentions may not lead to stronger subsequent self-efficacy beliefs is the experience of task failure. The theorized positive effect of intentions on self-efficacy hinges on the assumption that students experience mastery as part of the learning opportunities afforded by increased intentions. To the extent that students do not experience success in future learning contexts, intentions may not lead to increased self-efficacy beliefs. One profitable line of inquiry for future studies may be to investigate the mediating role of perceptions of mastery experiences in the pathway from intentions to self-efficacy.

Perhaps the most noteworthy set of results in the present study is the reciprocal links between math interest and math intentions over time. Specifically, the findings show that math interest predicted positive changes in subsequent math intentions, and math intentions predicted positive changes in subsequent math interests. These findings align with previous research demonstrating that math-related intentions and interests are correlated (Fouad & Smith, 1996; Navarro et al., 2007; Waller, 2006), and, importantly, extend this correlational evidence by disentangling the bidirectional effects underlying the math interest-intention link. The findings also align with previous research showing domain-general reciprocal links between vocational interests and intentions (Hirschi, 2010). Furthermore, the reciprocal effects found are consistent with the reciprocal determinism principle central to social cognitive theory, and extend the SCCT model by providing evidence that math interest and intentions may be mutually reinforcing in the educational and career choice process. For students who are interested during math tasks, the experience of enjoyment and heightened attention may foster the development of intentions related to math pathways as intentions are an expression of students' primary choice goals based on their interests. Intentions may, in turn, increase future interests by increasing the likelihood that students will opt into further math learning opportunities (Harackiwicz et al., 2008). In the educational choice process, interests and intentions may work together in a continuous positive feedback loop that guides the selection of academic and, ultimately, career pathways. Future research would do well to test this process, including the measurement of indices of students' educational choices.

Taken together, the findings of this study suggest that "plugging" the "leaky" school-to-career STEM pipeline necessitates consideration of not only students' math self-efficacy beliefs but also their math interests. Although some students many opt out of advanced math pathways in high school because they perceive lower competence in the domain, other students, who, despite having higher competence beliefs and requisite capabilities, may opt out of math pathways because they lack interest in math. Indeed, whereas the study findings suggest that self-efficacy beliefs are important to performance attainments, interests were shown be most important for subsequent intentions, which are known to influence educational and career choices (Perera & McIlveen, 2017; Schoon, 2001). Accordingly, the exclusive focus on enhancing math self-efficacy beliefs through meaningful practice may not be sufficient for helping students to navigate the major developmental task of choosing educational and career pathways, including those in math-related fields. Instead, math instruction tailored to the specific interests of different learners may be required to capture student interest in math and maintain its relevance and value to students through the secondary years (e.g., context personalization; Høgheim & Reber, 2015). Still, there is some evidence that interventions designed to promote math self-efficacy beliefs, based on Bandura's (1997) sources of self-efficacy, may also be useful in promoting math interests (Luzzo et al., 1999). Even more effective may be multicomponent motivational interventions, which seek to capitalize on the synergy between self-beliefs and interests rather than targeting individual motivational constructs. Effect sizes for interventions have been found to be larger when targeting multiple specific dimensions that are conceptually and logically linked to desirable outcomes (O'Mara, Marsh, Craven, & Debus, 2006).

Limitations

There are several limitations to this research that merit attention and serve to qualify the interpretation of results. First, although the design of the study is more robust than a cross-sectional design used in most other SCCT studies for inferring predictive relations, the two-wave data preclude tests of whether the construct interrelations have reached developmental equilibrium (Little et al., 2007); that is, whether the effects of one construct on another are consistent over. Examining developmental equilibrium hypotheses can yield important data on when developmental processes have attained equilibrium in a causal system. Future research should profitably examine the present longitudinal process model with multiple waves of data across several years to appropriately evaluate developmental equilibrium. In such work, optimal time lags between measurements are crucial (Dormann & Griffin, 2015), and should be informed by theory and/or appropriate pilot research. Furthermore, while we acknowledge the reliance of self-report for the measurement of most constructs, self-reports might be the most valid method for inferring individuals' self-perceptions related to their task-competence beliefs, interests, and goals. Nevertheless, multiple informant (e.g., teacher, parent) reports might provide additional insights into the motivational processes examined herein.

Outcome expectations were not examined in the present research, which constitutes another limitation of the research. In addition to self-efficacy, SCCT posits outcome expectations as a contributor to math interests and intentions (Smith & Fouad, 1999). Positive expectations should directly enhance interests and intentions. Within the SCCT, self-efficacy is regarded as an antecedent of outcome expectations; thus, conceptually at least, outcome expectations may carry, at least in part, the effects of self-efficacy to interest and intentions. Like self-efficacy, the SCCT proposes that outcome expectations are influenced by prior experience. Future research should include this construct in integrative models of the interplay among efficacy beliefs, expectations, interests, and intentions.

Next, although we accounted for the potentially confounding effects of gender through its inclusion as a covariate (i.e., accounting for mean level differences as a function of gender), we did not examine gender differences in the relations between the constructs (i.e., gender moderation effects) due to small male and female subsamples relative to model complexity. Indeed, increasingly, researchers are acknowledging that both approaches to investigating gender effects are required to fully understand gendered motivational processes involved in STEM-related educational attainments and choices (Eccles, 2009; Watt et al., 2012). Future researchers would do well to integrate both types of gender effects in examinations of the motivational processes postulated by the SCCT.

Another limitation of the research is the exclusive focus on individual-level student factors in the motivational processes examined. Although this student-level focus is consistent with much of the extant SCCT (and other motivational) literature (e.g., EVT), given the centrality of the interplay between self-referent thoughts and social processes in informing student behavior postulated in the social cognitive accounts of agency, it is entirely possible that students' math self-efficacy beliefs, interest, intentions, and achievement might be influenced, in part, by broader contextual-level factors, such as teacher and classroom characteristics (Arens & Morin, 2016; Zee & Koomen, 2016). Finally, though the use of a longitudinal panel design, with even two-waves of data, strengthens inferences of directionality and temporality of effects relative to cross-sectional data, we hasten to add that the predictive coefficients observed in the present study should not be interpreted as "causal" effects. The "omitted common cause" problem in longitudinal field studies provides an ample threat to causal inferences.

Conclusion

The present research makes a contribution to understanding math achievement and aspirations in early and middle adolescents. Our research replicates previous working in showing that, over and above the effects of prior achievement, math self-efficacy is a robust predictor of positive changes in math achievement. The research extends the motivational literature by showing, apparently for the first time, reciprocal relations between math interest and intentions, such that the constructs may be mutually reinforcing in choice-related developmental tasks. Furthermore, prior math interests positively predicted subsequent math self-efficacy beliefs. The strength of the inferences drawn from this study is supported by robust methodology, integrating models with latent variables, longitudinal data, and polytomous responses. Still, further work is required to better understand (a) when the relations observed herein reach development equilibrium, (b) the influence of gendered socialization process on the relations observed, and (c) the influence of school, classroom, and teacher factors on not only math achievement but also math self-efficacy beliefs, intentions, aspirations, and choices

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Table 1. Fit Statistics and Indices for the Longitudinal Invariance Models

Model	χ^2	*df*	CFI	TLI	RMSEA	90% CI	MD χ^2 (*df*)	ΔCFI	ΔRMSEA
Models with Class Grades									
LIM-1a (Configural)	372.950**	295	.992	.990	.026	.017, .033			
LIM-2a (IN λ)	380.763**	304	.993	.991	.025	.016, .033	9.099 (9)	+.001	-.001
LIM-3a (IN λ + ν)	413.686**	331	.992	.991	.025	.016, .032	52.912 (27)**	-.001	.000
LIM-4b (IN λ + ν + θ)	425.384**	343	.992	.991	.025	.016, .032	21.012 (12)	.000	.000
Models with Standardized Achievement									
LIM-1b (Configural)	370.547**	295	.993	.991	.025	.016, .033			
LIM-2b (IN λ)	378.405**	304	.993	.991	.025	.015, .032	9.106 (9)	.000	.000
LIM-3b (IN λ + ν)	411.440**	331	.992	.991	.025	.016, .032	53.186 (27)	-.001	.000

LIM-4b (IN $\lambda + \nu + \theta$)	423.690	343	.992	.991	.024	.015, .032	21.431 (12)*	.000	-.001

Note. N = 400. ** $p < .01$, * $p < .05$. df = degrees of freedom; MD χ^2 = change in χ^2 relative to the preceding model computed using the Mplus DIFFTEST function; ΔCFI = change in comparative fit index; ΔRMSEA = change in root mean square of approximation; LIM = Longitudinal invariance model; IN = invariance; λ= factor loadings; ν = Thresholds; θ = uniquenesses.

Table 2. (Standardized) Factor Loading Estimates from the Final Longitudinal Invariance Solutions

	Model with Class Grades		Model with Standardized Achievement	
	Wave 1	Wave 2	Wave 1	Wave 2
Math Self-efficacy				
MSE1	1.000 (.849)	1.000 (.882)	1.000 (.848)	1.000 (.881)
MSE2	0.999 (.849)	0.999 (.881)	1.007 (.849)	1.007 (.882)
MSE3	1.009 (.851)	1.009 (.883)	1.019 (.852)	1.019 (.884)
MSE4	0.632 (.713)	0.632 (.763)	0.637 (.713)	0.637 (.764)
MSE5	1.048 (.860)	1.048 (.891)	1.051 (.859)	1.051 (.890)
Math Interest				
MINT1	1.000 (.855)	1.000 (.890)	1.000 (.855)	1.000 (.891)
MINT2	0.936 (.839)	0.936 (.878)	0.933 (.839)	0.933 (.877)
MINT3	1.704 (.942)	1.704 (.958)	1.700 (.942)	1.700 (.958)
MINT4	1.305 (.907)	1.305 (.931)	1.300 (.907)	1.300 (.931)
Math Intentions				
MINS1	1.000 (.650)	1.000 (.715)	1.000 (.648)	1.000 (.714)
MINS2	1.398 (.767)	1.398 (.820)	1.409 (.768)	1.409 (.821)
MINS3	1.069 (.675)	1.069 (.738)	1.077 (.675)	1.077 (.739)

N = 400. MSE1-MSE5 = five math self-efficacy items; MINT1-MINT4 = four math interest items; MINS1-MINS3 = three math intentions items. Factor loadings are constrained to be invariant across the two waves in the unstandardized metric. Completely standardized coefficients are shown in parentheses. All loadings were statistically significant at $p < .001$.

Table 3. Fit Statistics and Indices for the Longitudinal Structural Equation Models

Model	χ^2	*df*	CFI	TLI	RMSEA	90% CI	MD χ^2 (*df*)	ΔCFI	ΔRMSEA
Models with Class Grades									
SM #1a	425.384**	343	.992	.991	.025	.016, .032			
SM #2a	423.444**	344	.992	.992	.024	.015, .031	0.568 (1)	.000	-.001
SM #3a	424.420**	345	.992	.992	.024	.015, .031	0.227 (1)	.000	.000
SM #4a	425.159**	346	.992	.992	.024	.015, .031	0.033 (1)	.000	.000
Models with Standardized Achievement									
SM #1b	423.690**	343	.992	.991	.024	.015, .032			
SM #2b	421.808**	344	.992	.992	.024	.015, .031	0.571 (1)	.000	.000
SM #3b	422.623**	345	.992	.992	.024	.015, .031	0.002 (1)	.000	.000

SM #4b	423.464**	346	.992	.992	.024	.015, .031	0.006 (1)	.000	.000

Note. N = 400. ** p < .01, * p < .05. df = degrees of freedom; MD χ^2 = change in χ^2 relative to the preceding model computed using the Mplus DIFFTEST function; ΔCFI = change in comparative fit index; ΔRMSEA = change in root mean square of approximation.

Table 4. Structural regression coefficients from the final structural model solution.

Variable	T1 Math Self-Efficacy	T1 Math Interest	T1 Math Intentions	T2 Math Self-Efficacy	T2 Math Interest	T2 Math Intentions	Math Achievement
			Model with Class Grades				
Gender	-0.926(-0.577)**	-0.422(-0.256)	-0.041(-0.048)	-0.140(-0.075)	-0.242(-0.124)	-0.233(-0.227)	0.626(0.626)***
Grade Level	-0.191(-0.119)*	-0.192(-0.116)	-0.080(-0.095)	-0.010(-0.005)	0.014(0.007)	-0.066(-0.064)	0.007(2.282)**
Prior Achievement	0.283(.394)***	0.151(.205)**	0.143(.373)***	0.069(.082)	0.020(.023)	0.013(.029)	0.597(.397)***
T1 Math Self-Efficacy	–	–	–	0.762(.655)***	0.050(.041)	0.003(.005)	0.544(.341)**
T1 Math Interest	–	–	–	0.186(.163)*	0.724(.609)***	0.123(.198)*	0.000(.000)

T1 Math Intentions	–	–	–	0.000(.000)	0.620(.271)*	0.737(.615)***	0.000(.000)
			Model with Standardized Achievement				
Gender	-0.921(-0.576)**	-0.422(-0.256)	-0.040(-0.047)	-0.133(-0.071)	-0.244(-0.124)	-0.234(-0.229)	-2.036(-2.036)***
Grade Level	-0.192(-0.120)*	-0.190(-0.115)	-0.080(-0.095)	-0.010(-0.005)	0.012(0.006)	-0.066(-0.064)	2.282(2.282)**
Prior Achievement	0.277(.392)***	0.152(.207)**	0.137(.362)***	0.065(.079)	0.020(.023)	0.015(.034)	1.153(.397)***
T1 Math Self-Efficacy	–	–	–	0.765(.657)***	0.051(.041)	0.002(.003)	0.919(.224)**
T1 Math Interest	–	–	–	0.183(.162)*	0.722(.608)***	0.122(.198)*	0.000(.000)
T1 Math	–	–	–	0.000(.000)	0.629(.273)*	0.738(.615)**	0.000(.000)

Intentions	*

Note. *N* = 400. *** p < .001, ** p < .01, * p < .01. Coefficients in parentheses are standardized coefficients. For continuous predictors, standardized coefficients are completely standardized using both the variances of the latent variables and predictors. For categorical predictors (i.e., gender, grade level), standardization is partial using only the variances of the latent variables.

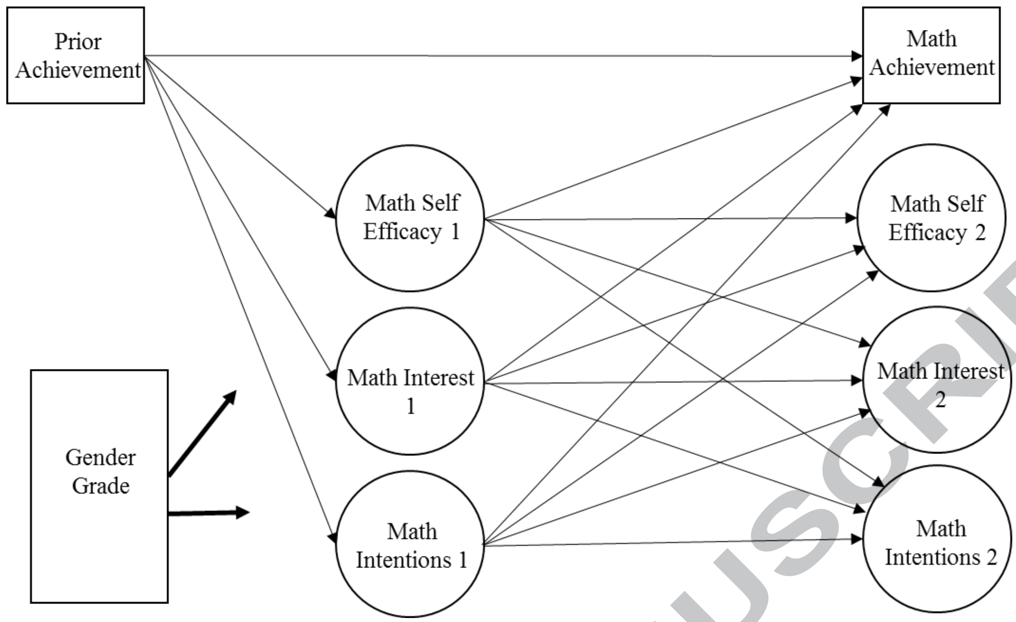

Figure 1. Schematic of the target structural model (SM #1) to be tested. Note. Covariance terms are not included in the model to avoid clutter. Furthermore, arrows from the covariates are stylistic, designed to suggest that the covariates have an effect on both T1 and T2 variables.

Appendix A

Descriptive Statistics and Correlations for the Manifest Variables

	C1/M	C2/SD	C3	C4	C5	C6	1	2
1. T1-MSE-1	.070	.347	.367	.216	–	–	–	
2. T1-MSE-2	.108	.385	.375	.131	–	–	.746	–
3. T1-MSE-3	.111	.319	.382	.188	–	–	.691	.844
4. T1-MSE-4	.063	.256	.407	.274	–	–	.756	.604
5. T1-MSE-5	.045	.247	.395	.312	–	–	.716	.713
6. T1-MINT-1	.245	.393	.285	.077	–	–	.430	.487
7. T1-MINT-2	.145	.307	.390	.158	–	–	.340	.393
8. T1-MINT-3	.226	.323	.291	.160	–	–	.473	.539
9. T1-MINT-4	.140	.233	.396	.231	–	–	.456	.505
10. T1-MINS-1	.013	.058	.068	.212	.340	.310	.358	.265
11. T1-MINS-2	.095	.105	.170	.268	.243	.118	.394	.399
12. T1-MINS-3	.106	.116	.196	.252	.156	.174	.354	.345
13. T2-MSE-1	.070	.231	.472	.226	–	–	.730	.607
14. T2-MSE-2	.101	.357	.377	.166	–	–	.661	.669
15. T2-MSE-3	.101	.362	.317	.221	–	–	.659	.622
16. T2-MSE-4	.045	.151	.462	.342	–	–	.567	.444
17. T2-MSE-5	.055	.196	.422	.327	–	–	.638	.562
18. T2-MINT-1	.266	.382	.236	.116	–	–	.509	.527
19. T2-MINT-2	.146	.312	.372	.171	–	–	.480	.431
20. T2-MINT-3	.216	.337	.261	.186	–	–	.510	.508

21. T2-MINT-4	.151	.266	.357	.226	–	–	.491	.484
22. T2-MINS-1	.030	.056	.056	.212	.303	.343	.365	.247
23. T2-MINS-2	.126	.121	.162	.283	.167	.141	.467	.383
24. T2-MINS-3	.086	.117	.122	.264	.208	.203	.381	.322
25. Prior Ach	10.659	2.284	–	–	–	–	.343	.333
26. Class Grades	10.473	2.566	–	–	–	–	.483	.427
27. Stan. Ach	60.312	6.556	–	–	–	–	.243	.302

	3	4	5	6	7	8	9	10
3. T1-MSE-3	–							
4. T1-MSE-4	.602	–						
5. T1-MSE-5	.721	.617	–					
6. T1-MINT-1	.520	.450	.487	–				
7. T1-MINT-2	.407	.268	.404	.694	–			
8. T1-MINT-3	.508	.494	.504	.809	.808	–		
9. T1-MINT-4	.515	.430	.545	.763	.776	.835	–	
10. T1-MINS-1	.201	.249	.345	.304	.400	.411	.455	–
11. T1-MINS-2	.401	.270	.409	.465	.433	.519	.541	.492
12. T1-MINS-3	.386	.260	.365	.446	.413	.491	.494	.349
13. T2-MSE-1	.551	.494	.589	.402	.408	.451	.446	.377
14. T2-MSE-2	.615	.476	.617	.502	.357	.471	.448	.316
15. T2-MSE-3	.593	.472	.609	.505	.488	.528	.512	.306

16. T2-MSE-4	.508	.634	.422	.354	.370	.448	.436	.271
17. T2-MSE-5	.495	.468	.637	.429	.408	.512	.524	.407
18. T2-MINT-1	.481	.443	.413	.717	.589	.692	.585	.410
19. T2-MINT-2	.372	.403	.411	.683	.699	.735	.651	.402
20. T2-MINT-3	.442	.427	.469	.715	.691	.770	.700	.469
21. T2-MINT-4	.422	.287	.496	.699	.599	.683	.675	.488
22. T2-MINS-1	.188	.249	.331	.437	.473	.454	.450	.632
23. T2-MINS-2	.408	.322	.361	.510	.385	.471	.405	.430
24. T2-MINS-3	.353	.260	.336	.453	.381	.473	.422	.388
25. Prior Ach	.318	.177	.341	.166	.192	.198	.181	.252
26. Class Grades	.420	.308	.467	.217	.291	.304	.295	.391
27. Stan. Ach	.311	.209	.218	.183	.131	.158	.077	.068

	11	12	13	14	15	16	17	18
11. T1-MINS-2	–							
12. T1-MINS-3	.569	–						
13. T2-MSE-1	.359	.347	–					
14. T2-MSE-2	.394	.314	.800	–				
15. T2-MSE-3	.408	.304	.772	.873	–			
16. T2-MSE-4	.319	.301	.691	.687	.700	–		
17. T2-MSE-5	.399	.314	.812	.764	.821	.711	–	
18. T2-MINT-1	.531	.451	.512	.521	.522	.432	.487	–

19. T2-MINT-2	.488	.349	.563	.516	.608	.490	.588	.784
20. T2-MINT-3	.584	.462	.537	.570	.599	.518	.586	.822
21. T2-MINT-4	.564	.448	.595	.601	.630	.524	.628	.770
22. T2-MINS-1	.421	.283	.525	.414	.505	.399	.597	.574
23. T2-MINS-2	.548	.394	.490	.507	.548	.417	.502	.581
24. T2-MINS-3	.553	.688	.451	.452	.462	.439	.491	.499
25. Prior Ach	.245	.248	.339	.286	.152	.247	.288	.131
26. Class Grades	.276	.242	.402	.333	.257	.180	.314	.248
27. Stan. Ach	.178	.148	.199	.345	.324	.241	.253	.234

	19	20	21	22	23	24	25	26	27
19. T2-MINT-2	–								
20. T2-MINT-3	.899	–							
21. T2-MINT-4	.857	.890	–						
22. T2-MINS-1	.604	.646	.629	–					
23. T2-MINS-2	.583	.677	.555	.578	–				
24. T2-MINS-	.531	.634	.548	.483	.639	–			

3									
25. Prior Ach	.229	.282	.295	.235	.213	.226	–		
26. Class Grades	.354	.365	.352	.303	.297	.217	.641	–	
27. Stan. Ach	.256	.286	.237	.108	.205	.197	.380	.403	–

Note. C1/M = Category 1 proportion for polytomous item or mean for continuous item. C2/SD = Category 2 proportion for polytomous item or standard deviation for continuous item; C3 = Category 3 proportions; C4 = category 4 proportion; C5 = Category 5 proportion; C6 = Category 6 Proportion. T1 = Time 1; T2 = Time 2; MSE-1-MSE-5 = five math self-efficacy items; MINT-1-MINT-4 = four math interest items; MINS-1-MINS-3 = three math intentions items; Prior Ach = Prior achievement; Stan. Ach = Standardized achievement.

Highlights

- We examined a social-cognitive model linking math self-efficacy, interests, intentions, and achievement over a six-month period
- Analyses were conducted using fully-latent structural equation models, including tests of longitudinal invariance with ordered categorical data
- Results showed that math self-efficacy was a significant positive predictor of changes in math achievement using both class grades and standardized test score operationalizations
- Prior math interests predicted positive changes in subsequent math self-efficacy
- Math interest and math intentions are found to be reciprocally related