Learning and Individual Differences 26 (2013) 119–130

Contents lists available at SciVerse ScienceDirect

Learning and Individual Differences

journal homepage: www.elsevier.com/locate/lindif

Higher-order structure of noncognitive constructs and prediction of PISA 2003 mathematics achievement

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ARTICLE INFO

Article history:
Received 15 September 2011
Received in revised form 12 March 2013
Accepted 13 May 2013

Keywords:
Motivation
Self-beliefs
Self-efficacy
Self-concept
Learning strategies
Attitudes toward school

ABSTRACT

The present study investigates higher-order factor structure among fifteen primary variables selected from four broad noncognitive domains of academic self-beliefs, motivation, learning strategy, and attitudes toward school. The PISA 2003 international dataset was analyzed. Several EFA, CFA, and SEM models were tested, hypothesizing the structure among the primary first-order variables and their relationships to the mathematics scores. The analyses indicated no single, general factor at the second-order level, encompassing all fifteen first-order variables. Instead, the fifteen primary variables were best represented by a three-level factor structure with the four salient domain factors at the second-order level and one general noncognitive factor at the third-order. The most plausible SEM model had each of the three self-belief primary variables individually linked to the mathematics achievement scores, independent of the third-order factor. Self-efficacy was the strongest predictor of mathematics achievement and its predictive power was comparable to that of the common part of all 15 primary variables captured by the general noncognitive factor.

Within the subfields of psychology such as intelligence and personality, there has been a long history of examining the structure of their "major" constructs. In contrast, ever since the concept of motivation gained its prominence (e.g., Atkinson, 1957, 1964; Cofer & Appley, 1967; Goldthorpe, Lockwood, Bechhofer, & Platt, 1968; Vroom, 1964), there has been relatively little interest in educational psychology to identify the overall structure of its well-established psychological constructs. By "major" constructs, we mean those constructs that have been well-defined theoretically and empirically, that have "survived" years of rigorous research, and have proven strong links to meaningful outcome measures such as academic achievement. Many psycho-educational constructs with such properties have been identified in a recent review paper (Lee & Shute, 2010). Researchers have also continued to highlight considerable (empirical and theoretical) commonalities among them (cf, Martin, 2007, 2009). The goal of the present study is (1) to investigate the overall structure underlying a group of major student-related psychological constructs that have relevance to education, and (2) to assess the effectiveness of the structure in predicting students' academic achievement. We examine whether the fifteen psychological constructs selected for this study can be reduced to a smaller number of domains and whether there is one general, higher-order construct that can reasonably represent them.

1. PISA 2003 data source

The present study adopts the 2003 data of a large-scale international survey, known as the Programme for International Student Assessment (PISA) (see OECD, 2004a).[1] Fifteen psychological constructs measured in the PISA 2003 assessment were employed in the present study. Those constructs are: interest in math; instrumental motivation in math; math self-efficacy; math self-concept; math anxiety; control; elaboration; memorization; competitive learning; cooperative learning; attitudes toward school; student–teacher relationships; sense of belonging to school; teacher support in math lessons; and disciplinary climate in math lessons (see Appendix 1 for definitions of each construct and the questionnaire items). We label all fifteen constructs collectively as "noncognitive" constructs. We use the term "noncognitive" in the way that was conceptualized in Bowles and Gintis (1976, 2000, 2002), Farkas (2003) and Messick (1979). In their definition, noncognitive constructs are referred to as all psychological and behavioral dispositions, tendencies, and habits that are not measured by typical cognitive tests such as tests of school performance,

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[1] Test/survey developers in a well-established large-scale assessment (e.g., PISA) follow an extensive procedure to select the variables for their survey instruments. The variables are selected based on their conceptual clarity, well-defined factorial structure, and strong psychometric properties, and should have clear relevance to academic achievement and be known to be amenable to change through meaningful interventions. Leading experts in diverse fields (e.g., education, psychology, sociology, economics, cross-cultural psychology, and measurement/evaluation) participate in the variable selection process. As a result the selected variables tend to reflect different theoretical backgrounds.

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http://dx.doi.org/10.1016/j.lindif.2013.05.004

ability, and aptitudes. We recognize that noncognitive constructs have a component of cognition. Similarly, cognitive skills require some level of noncognitive capacity. Thus, cognitive and noncognitive variables are typically correlated with each other. It is a usually a matter of degree: there is hardly any construct that is "purely" cognitive or "purely" noncognitive (Farkas, 2003).

The fifteen constructs examined in this study have been traditionally explored within four broad domains or theoretical streams, namely, motivation, self-beliefs, learning strategies/preferences, and attitudes towards school, which are the building blocks of the present study. Motivation constructs have evolved from expectancy-value theory (Atkinson, 1957; Eccles, Midgely, & Adler, 1984; Elliot & Dweck, 2005; Vroom, 1964; Wigfield & Eccles, 2000), intrinsic and extrinsic motivation (Deci & Ryan, 1992; Lepper, Corpus, & Iyengar, 2005; Schwinger, Steinmayr, & Spinath, 2009); theory of performance-contingent rewards (e.g., Bandura, 1986, 1997; Cameron, Pierce, Banko, & Gear, 2005; Schunk, 1991), attribution (Weiner, 1986), goal orientation (Ames, 1992; Elliot & Harackiewicz, 1996), and interest development (Krapp, 2005; Renninger, Hidi, & Krapp, 1992). Two extensively studied motivational constructs, intrinsic (interest in math) and extrinsic motivations (instrumental motivation in math), are employed in the current study. The two self-beliefs constructs that have received much attention in relation to student achievement are arguably: self-concept (Harter, 1985a, 1985b; Marsh, 1986, 2007) and self-efficacy (Bandura, 1986, 1997; Pajares, 1996; Schunk, 1991). In addition, emotional regulation and affective aspects of self are often indexed by students' tendency to feel anxious when they face specific academic tasks (i.e., anxiety) (Pekrun, Goetz, Titz, & Perry, 2002; Schutz & Davis, 2000; Schutz & DeCuir, 2002). These three self-related constructs are included in the present study. Advances in the conceptualization of learning strategies were made within the theoretical framework of self-regulated learning (Mayer, 1998; Pintrich, 2000; Schunk & Zimmerman, 2003; Zimmerman, 1990, 2001), which emphasizes control/metacognition, elaboration, and review/rehearsal/memorization (e.g., Borkowski, Johnston, & Reid, 1986; Cardelle-Elawar, 1992). Two types of learning style, cooperative and competitive learning, have gained much attention of researchers and practitioners (see Johnson & Johnson, 1989; Slavin, 1980, 1996). These five constructs can be grouped as approaches to learning. Social-cognitive theory (Bandura, 1986, 1997; Goodenow, 1992, 1993) highlights the critical roles that teachers play in shaping students' attitudes toward school (Elliot & Dweck, 2005; Radel, Sarrazin, Legrain, & Wild, 2010), student–teacher relationships (Den Brok, Brekelmans, & Wubbels, 2004; Wentzel, 1994) and students' sense of belonging at school (Finn, 1989; Goodenow, 1992, 1993; Voelkl, 1997). These constructs are related to students' general attitudes toward school, classroom, and teachers. Five such constructs are employed in the present study. The present study aims to establish whether the individual fifteen constructs, which have been extensively studied within these theoretical approaches, can be meaningfully related to each other and understood within a broader structural framework.

2. Conceptualizing a higher-order structure

Many empirical studies have hinted at the possibility of a higher-order structure among the major four domains of constructs that are the focus of this paper — i.e., motivation, self-beliefs, learning strategies/preferences, and attitudes towards school. First, there may be higher-order constructs within the domain-level. Marsh and his colleagues (Marsh, Hau, Artelt, Baumert, & Peschar, 2006) showed that primary constructs of academic self-beliefs had substantial correlations with each other (e.g., correlations between .66 and .91 among academic self-concept, self-efficacy, and control expectations). Other studies (e.g., Lee, 2009; Pajares & Miller, 1994) reported similar (or even higher) correlations among the variables belonging to the same domain, suggesting the presence of a higher-order factor among the within-domain variables.

Second, it is often reported that there are substantial correlations among the constructs across the four domains. For example, the motivation constructs in the PISA 2000 data were substantially related to all three learning strategies variables — i.e., control, elaboration, and memorization ($rs = .52$ to $.93$) (Marsh et al., 2006). Similarly, these learning strategy variables showed substantial correlations with the academic self-beliefs variables ($rs = .67$ to $.76$). Martin (2007) also found that the constructs of self-beliefs, intrinsic motivation, and attitudes toward school were all substantially correlated with each other ($rs = .73$ to $.79$). He also noted that students' attitude toward school was substantially correlated ($r = .51$ and $.58$) with their use of learning strategy in planning and task management (Martin, 2009). The substantial size of cross-domain correlations is suggestive of a potential higher-order structure among the domain-level constructs. In other words, the commonality (i.e., shared variances) among the cross-domain constructs can be captured by a broader construct.

Third, from the theoretical point of view, the four constructs at the domain-level tend to share antecedents and are linked to the same or similar types of outcome variables (see the following three sections describing the conceptual links). Furthermore, the item content across the four domains (see Appendix 1) seems to have substantial overlap and may be open to questions about their face validity. For instance, "I am just not good at mathematics" and "I worry that I will get poor marks in mathematics" belong to different domain level constructs (self-concept versus anxiety).

In sum, previous studies (Lee, 2009; Marsh et al., 2006; Martin, 2007, 2009; OECD, 2004a) have reported substantial correlations among the variables within and across the theoretical domains of interest in this paper. The domain-level variables have been linked to similar types of antecedents and outcomes. This observation suggests that there may be an overarching structure that can capture the relationships within and across the domain-level variables.

In the following sections we elaborate on some of the theoretical accounts about how the four domain-level constructs relate to each other. We then present empirical evidence about their particular relationship to academic achievement.

3. Conceptual links between motivation and self-beliefs

Motivation (e.g., Atkinson, 1957; Eccles et al., 1984; Elliot & Dweck, 2005; Schunk, 1991; Skinner, Furrer, Marchand, & Kindermann, 2008; Vansteenkiste, Lens, & Deci, 2006; Vroom, 1964; Wigfield & Eccles, 2000) directs and drives one's mental and emotional energy and efforts to work toward attaining the goal. It is characterized by desire, persistence, and expectations for success, which governs one's behavior toward achievement by planning, monitoring and regulating. In the expectancy-value theory of motivation (Atkinson, 1964; Wigfield & Eccles, 2000), self-belief is one of the critical components of motivation. The theory asserts that motivation to do well in a particular task is linked to individuals' perception of the likelihood of obtaining positive outcomes (i.e., perceived outcome expectancy), their perceived competency in mastering the task by their own abilities (self-efficacy), and their personal, intrinsic values to the particular task (e.g., Becker, McElvany, & Kortenbruck, 2010; Deci & Ryan, 1992; Vansteenkiste et al., 2006). Some researchers (e.g., Bandura, 1997; Pajares, 1996) see academic self-beliefs (self-efficacy in particular) as an active state of motivation (cf, Martin, 2007). Intrinsic motivation and self-beliefs often coexist in one's desire to do well on a particular task (Schunk, 1991). Thus, if these two constructs of motivation and self-beliefs are examined with a large set of measures, it is possible that a high-level of commonality between them will make it hard to tease them apart empirically.

Research has also indicated that motivation and academic self-beliefs share the same antecedents and are linked to a common set of outcome variables. These antecedents include: positive feedback, observation of progress, perceived control, social contexts, attributions of outcomes to effort, incremental views of ability, and performance-contingent rewards (Bandura, 1986, 1997; Cameron et al., 2005; Schunk, 1991). Both motivation and self-beliefs tend to be linked to outcome variables such as academic performance, achievement-oriented behaviors, and effort and persistence (cf, Schunk, 1991). It is also known that emotional aspects of learning (e.g., anxiety, boredom, and liking) play a role in one's motivation and self-belief in succeeding in a particular task (Pekrun et al., 2002; Schunk, 1991; Schutz & Davis, 2000; Schutz & DeCuir, 2002).

4. Conceptual links between motivation, self-beliefs, and learning strategies

Self-regulated learning theory (Schunk & Zimmerman, 2003; Zimmerman, 1990, 2001) shows how variables from the three domains of motivation, self-beliefs, and learning strategies are tied together and ultimately produce desirable outcomes. Motivated students tend to be self-regulated learners, who are willing to employ different types of learning strategies, evaluate effectiveness of their learning, closely monitor their learning progress, and modify their learning habits if progress has not been made (Schunk, 2001; Zimmerman, 2001). When students perceive that their use of learning strategies has been effective and consequently their learning goals are being met, their sense of self-beliefs in learning can be nourished, which can also motivate them further to become more self-regulated learners (Mayer, 1998; Pintrich, 1986; Schunk, 1991).

Many other studies also postulated close relationships between students' self-belief in learning and their use of learning strategies (Bandura, 1997; Borkowski et al., 1986; Clayton, Blumberg, & Auld, 2010; Pintrich & De Groot, 1990; Schunk, 1989, 1991; Zimmerman & Martinez-Pons, 1990). For instance, students with positive self-efficacy tend to engage in cognitively-oriented learning behaviors (elaboration, rehearsing, organizing, planning) as well as metacognitive skills (monitoring progress, managing effort, and knowing what they have learned) (e.g., Pintrich & De Groot, 1990; Schunk, 1989). Recent studies (e.g., Schwinger et al., 2009) continue to show the mediating role that learning strategies play on the effects of motivation and self-beliefs on academic achievement.

5. Conceptual links between motivation, self-beliefs, learning strategies, and attitudes toward school

Social-cognitive theory of learning (e.g., Bandura, 1986; Deci & Ryan, 1992; Goodenow, 1992) highlights the importance of social contexts in students' academic motivation and learning outcomes. Social contexts in education settings are typically represented by school environment (e.g., competitive or cooperative), teacher–student relationships, peer norms, and evaluation system in a particular school (Bandura, 1986; Goodenow, 1992; Schunk, 1991; Skinner & Belmont, 1993; Skinner et al., 2008). For instance, students' sense of competence and self-beliefs in academic abilities can be modified or enhanced by support and praise from teachers or by comparison with peers (Bandura, 1986). Students' perception of the relationships with their teachers is correlated with their engagement at school (Skinner & Belmont, 1993; Skinner et al., 2008), academic motivation (Krapp, 2005; Soric & Palecic, 2009), self-beliefs (Bandura, 1986; Goodenow, 1992; Schunk, 1991), and sense of control and competence (Goodenow, 1993; Radel et al., 2010; Voelkl, 1997). For instance, when teachers are perceived to be warm, supportive, and responsive, students may feel confident about themselves and be intrinsically motivated in learning and expect good learning outcomes (e.g., Den Brok et al., 2004; Goodenow, 1992, 1993; Wentzel, 1994). Teachers' own attitude during lessons is also linked to students' intrinsic motivation in the classroom (Atkinson, 2000; Radel et al., 2010; Wild, Enzle, & Hawkins, 1992). Furthermore, school contexts and teachers provide the sources of cognitive-modeling for students to learn about various learning strategies (Schunk, 1991; Skinner & Belmont, 1993; Soric & Palecic, 2009). If classroom activities are centered on reflection and discussion, students may realize the ineffectiveness of memorization (Schunk, 1991; Skinner & Belmont, 1993; Soric & Palecic, 2009). Thus, teachers' teaching style can be a model for students' learning strategies (Soric & Palecic, 2009).

6. Summary

As shown in previous sections, both empirical and theoretical accounts support the links among the constructs of interest in this study. They are not only related to each other, but also share a common set of antecedents and outcome variables. This points to the need to examine a potential higher-order structure. The links suggested in the extant research thus far are mainly cyclic and they are associations at best. Little research has been conducted to examine the overall structure among the constructs in our chosen domains. The overall structure among them will show particular types of relationship, for instance, a higher-order construct encompassing all fifteen constructs may exist. Such an approach will clarify the relationship among the major educational psychology constructs that are known to be of relevance for academic achievement. We now turn our attention to how the domain constructs are related to our outcome variable, academic achievement.

7. Relationship between the four noncognitive domain constructs and academic achievement

An abundance of literature in education has documented the relationship between the four major domain constructs and academic achievement (see also Lee & Shute, 2010 for a comprehensive review of the relationships of these constructs). We describe in this section a summary of key findings from the recent PISA studies as background information for the current investigation.

7.1. Motivation and academic achievement

PISA studies (conducted in a three-year cycle since 2000) have consistently shown that students' intrinsic motivation (i.e., interest and enjoyment) were significantly and positively related to their academic performance (OECD, 2003, 2004a, 2010). For instance, the PISA 2009 assessment shows that a one unit change in the interest scale is associated with on average a 40-point increase in reading achievement (OECD, 2010). In PISA 2003, one unit change in the interest and enjoyment of mathematics scale is associated with on average a 12-point increase in mathematics performance (OECD, 2004a). PISA studies tend to show that interest and enjoyment had a stronger association with reading than with mathematics, which was also evident in Marsh et al. (2006). Students' extrinsic motivation was also linked to positive school outcome. Overall, instrumental (extrinsic) motivation has a relatively weaker relationship to academic performance than intrinsic motivation does, which is consistent with the intrinsic–extrinsic motivation literature (e.g., Becker et al., 2010; Lepper, 1983; Lepper et al., 2005).

7.2. Self-beliefs and academic achievement

Predictive power of self-beliefs on students' academic achievement has been well documented (e.g., Lee, 2009; Lee & Shute, 2010; Marsh et al., 2006; OECD, 2004a). For instance, Marsh et al. (2006) report moderately strong associations between both reading and mathematics achievement and self-concept of the corresponding domains ($r = .30$ between verbal self-concept and reading; $r = .33$ between math self-concept and mathematics). Self-concept and self-efficacy measured in the context of academic achievement in general had a similar range of correlations for both reading and mathematics scores (ranging from .27 to .34). Similarly Lee (2009), based on the PISA 2003 dataset, highlights fairly strong relationships between mathematics achievement and three mathematics-related self-belief constructs (i.e., r = .41 with math self-efficacy; r = −.39 with math anxiety; and somewhat lower r = .23 with math self-concept). Recent studies also point to the importance of self-belief measures in predicting academic achievement (Stankov, Lee, Luo, & Hogan, 2012; Stankov, Morony, & Lee, in press).

7.3. Learning strategy use and academic achievement

Learning strategy can be broadly defined. It includes any plans or strategies that "students select to achieve their <learning> goals" (Haahr, 2005, p. 121). Three types of learning strategies have been recognized as the key learning strategy variables in PISA 2000 and 2003 studies (OECD, 2001, 2004a) and elsewhere (e.g., Cardelle-Elawar, 1992; Carr, Borkowski, & Maxwell, 1991; Pintrich & De Groot, 1990; Pokay & Blumenfeld, 1990). They are: control (e.g., figuring out what they need to know, clarifying what they did not understand), elaboration (e.g., relating new to previous knowledge; applying school learning to real-world situations), and memorization. Moderately strong relationships were found between the PISA academic achievement measures and students' use of control and elaboration strategies (OECD, 2010). For example, about 8% of the variance in the PISA 2009 reading achievement was explained by students' use of control strategies alone (OECD, 2010). Additionally, there were increases of 26 points and 7 points in the PISA reading tests associated with one unit change on the control and elaboration scales, respectively (OECD, 2001, 2010). On the other hand, the effect of memorization on academic achievement has been unclear or negative. A general trend shown in PISA studies (OECD, 2001, 2004a, 2010) is that control strategies had stronger associations with both reading and mathematics than memorization or elaboration. Control strategies also showed a stronger relationship to reading than mathematics achievement (OECD, 2001, 2004a, 2010).

Findings about the relationship between academic achievement and the students' preference in learning style (i.e., preferences for cooperative learning and competitive learning) have been inconclusive in the 2000 and 2003 PISA assessments. It has been conjectured that it could be because both learning situations are not mutually exclusive (Haahr, 2005). Regardless of individuals' preference in learning style, students typically engage in some group activities in the school settings and have to produce a certain type of individual performance. It appears that students in the high-performing countries (Finland, Korea, Japan, Belgium, and Netherlands) tended to be at the bottom in terms of liking for or engaging in cooperative learning style. Ironically, these countries (except Korea) also showed disliking of (or not pursuing) learning based on individuals' drive for competition. Thus, this (i.e., students in the high-performing countries not being engaged in either cooperative or competitive learning) could obscure a pattern of the relationship between these two types of learning style and academic performance.

7.4. Attitudes towards school and academic achievement

Substantial associations between students' attitudes toward school and their academic outcomes have been shown in the PISA assessment, especially when the analysis is conducted at the school-level. That is, schools associated with a high-level of a sense of belonging to school tend to show better academic performance at the school level (OECD, 2003, 2004a). This school-level correlation between students' sense of belonging and academic achievement was both consistent and substantial across various subject areas: reading (r = .51), mathematics (r = .48), and science (r = .50) in the PISA 2000 data (OECD, 2003). Correlations of this magnitude are typically found between academic motivation and achievement (cf, OECD, 2003).

When the measurement unit is at the student-level, there has been no clear-cut finding of psychological effects related to teachers and schools. For instance, a positive relationship was established between academic achievement and schools' disciplinary climate. The increase on the mathematics achievement was nearly 18 points by one unit change on the schools' disciplinary climate scale (OECD, 2004a). However, students' perception of teacher-support was not positively related to their mathematics achievement (OECD, 2004a, p.213). It appears that this negative relationship could be because students in the high-performing countries (such as Japan, Germany, Netherland, and Korea) tended to be critical about the support that they received from their teachers and schools.

8. Purpose of the current investigation

Although literature points out that the constructs from the four noncognitive domains in our study are substantially related to each other, it has been relatively rare that studies consider the structural approach to understand their multivariate effects. To the best of our knowledge, no such studies have been conducted based on large-scale data. The main focus of the current study is to:

1. Examine the higher-order structure among the fifteen primary factors, which have been extensively studied as educationally important noncognitive constructs. Two issues will be addressed:
   a. Are the four domains – academic self-beliefs, motivation, learning strategies/preferences, and attitudes toward school – supported by the second-order structure?
   b. Is there a third-order, general factor?
2. Examine predictive validity of first-, second- and third-order factors for PISA mathematics achievement scores. The focus of most previous work has been on the strength of the pathways from individual constructs to the outcome measures. Thus, the present study will:
   a. Test the utility of the higher-order model(s) for predicting achievement in mathematics.
   b. Identify the best predictor(s) at the appropriate level (i.e., at the first-, second-, or third-order level) that show the best predictive validity for mathematics achievement.

9. Method

9.1. Data and sample

The present study employed the PISA 2003 international data, with a total number of participants of more than a quarter million (N = 255,368) from 41 countries. The data were downloaded from the official PISA website (currently at http://pisa2009.acer.edu.au/). The analyses reported in this paper are based on the total PISA sample. The target population was 15 year-old students who attended formal schooling at the time of the PISA 2003 assessment.

9.2. Variables

All fifteen education-related psychological variables measured in the PISA 2003 student questionnaire were employed in this study as our first-order variables (listed in the introduction section). They were constructed at the scale-level, with each variable consisting of four to eight items (see Appendix 1 for the actual items). These primary, first-order variables were the standardized scale-scores with a mean of 0 and a standard deviation of 1. The majority of the constructs were measured in the context of learning mathematics. Thus mathematics achievement scores were employed as an outcome measure relating to these psychological variables. The original PISA mathematics achievement score was scaled with a mean of 500 and a standard deviation of 100. In our analyses, the mathematics scale-score was converted to a z-score (mean of 0 and a standard deviation of 1) in order to place it in the same metric as the metric used with fifteen psychological variables. In this study we employed mathematics achievement as a proxy for academic achievement. This is especially applicable to the PISA academic tests as they aim to measure a broad range of knowledge and application skills situated in various real-world contexts (OECD, 2001). Empirical evidence supports this intended purpose. There is a strong general intelligence factor measured in PISA academic tests: correlations between subject domains are between the high .70s and high .80s. ($r = 0.77$ between Reading and Mathematics; $r = 0.83$ between Science and Reading and Mathematics; and $r = 0.89$, 0.82, and 0.80 between Problem solving and Mathematics, Reading and Science, respectively, OECD, 2004b, p. 55).

The psychometric properties of each of the fifteen scales are strong in terms of factorial robustness, reliability, IRT criteria, and associations with achievement scores (OECD, 2004a, 2005). There were a few negatively worded items on the ATSCHL, BELONG, SCMAT, and DISCLIM scales (e.g., I feel like an outsider), which were reversely coded and appropriately scaled. It is important to keep in mind that positive values on the scales mean that the scores were higher than the average scale score of the OECD countries and do not reflect "positive" attitudes on the particular scale (OECD, 2004a).

9.3. Statistical analysis

We employed both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) methods. EFA was used to examine the structure among the fifteen psychological scales. CFA was used to: a) confirm the structure obtained through EFA; b) examine the hierarchical structure of our four major psychological domains; and c) investigate the effects of our fifteen primary variables on academic achievement (i.e., mathematics scores) using the structural equation modeling (SEM) approach. The maximum likelihood procedure was used in EFA, CFA and SEM analyses. Correlation matrix was the input for the EFA whereas the covariance matrices were entered as the input of CFA and SEM. All analyses reported in this paper were carried out using Mplus software (see Muthén & Muthén, 2007).

10. Results

In preliminary analyses, we used both EFA and CFA to examine the structure at the item-level with 75 statements listed in Appendix 1. The fifteen primary scales were confirmed as separate factors. We use them (the fifteen primary scales) as the base for the first-order structure and as building blocks for the subsequent, higher-order (second- and third-order) modeling. The properties of the scales were also reported in OECD (2004a, 2005). In order to save space, we do not present here the solution at the first level.

10.1. Correlations among the fifteen primary scales

Correlations among the primary scales (i.e., first-order variables 1 to 15 in Table 1) showed a wide range of values indicating varying levels of strength of associations (i.e., from nearly zero to >.60). The signs of all correlations were in the expected direction (i.e., all positive except for those of math anxiety). Patterns of correlations were generally within the theoretical expectations of the four major domains. That is, moderate to substantial sized correlations were found between the within-domain variables. For instance, the correlations among the self-beliefs scales (i.e., self-efficacy, anxiety and self-concept) ranged between .40 and .60. The two motivational constructs, although one is an aspect of intrinsic motivation (interest) and the other measures extrinsic motivation (instrumental motivation), were also substantially and positively correlated ($r = .60$). On the other hand, the five scales of attitude toward school showed relatively small within-domain correlations.

As expected, some moderately strong "cross-over domain" correlations were found. In particular, two motivation variables (interest and instrumental motivation) correlated with several other scales of the cross-domain variables (e.g., rs = .64 and .43 with self-concept; rs = .50 and .46 with elaboration strategies; and rs = .47 and .45 with competitive learning).

Table 1 also presents correlations between the fifteen primary scales and the PISA 2003 mathematics achievement scores (variable 16). As can be seen, the highest correlations are found with the three mathematics self-belief variables. Most other scales have correlations lower than .10. The lowest negative correlations are found with the measures of two domains — learning strategies/preferences and attitude toward school.

10.2. Second-order structure among the fifteen primary scales

10.2.1. Exploratory factor analysis (EFA) results

The correlational matrix among the fifteen primary variables presented in Table 1 was the input into the EFA analysis , which examines the structure at the second-order level. Four factors were extracted based on root-one criterion, with 47% cumulative

Table 1
Bivariate correlations among the fifteen PISA 2003 scales employed in this study (N = 255,368).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Math self-efficacy	1														
2. Math anxiety	−.403	1													
3. Math self-concept	.502	−.637	1												
4. Interest in math	.324	−.328	.635	1											
5. Instrumental motivation in math	.284	−.179	.429	.601	1										
6. Control strategies	.274	−.004	.261	.357	.376	1									
7. Elaboration strategies	.277	−.066	.369	.499	.457	.538	1								
8. Memorization strategies	.207	.002	.274	.368	.361	.589	.527	1							
9. Competitive learning	.239	−.064	.385	.470	.447	.423	.494	.459	1						
10. Cooperative learning	.146	.037	.135	.233	.260	.369	.375	.335	.347	1					
11. Attitudes towards school	.111	−.037	.151	.275	.332	.294	.250	.239	.224	.188	1				
12. Student–teacher relations	.109	−.055	.168	.317	.303	.264	.245	.241	.212	.200	.393	1			
13. Sense of belonging to school	.175	−.140	.109	.070	.153	.202	.101	.122	.081	.200	.281	.244	1		
14. Teacher support in math class	.108	−.080	.204	.318	.292	.237	.261	.239	.233	.197	.264	.434	.142	1	
15. Disciplinary climate in math class	.118	−.132	.110	.141	.085	.081	−.005	.032	.005	.008	.145	.158	.086	.162	1
16. Math achievement score	.468	−.375	.280	.008	.007	−.044	−.129	−.101	−.068	−.078	−.060	−.074	.034	−.086	.160
Standardized regression coefficients for predicting mathematics achievement score (R-square = .330)	.445	−.161	.145	−.151	.027	.013	−.175	−.051	−.047	−.006	−.018	−.025	−.037	−.066	.110

Note. All correlations are significant at the 0.01 level except .002, −.004, .005, and .008.

percentage of total variance being accounted for. The factor loadings from this second-order EFA are presented in Table 2 (with values smaller than .25 omitted). As can be seen, the four extracted factors correspond to the four major domains of mathematics self-beliefs, motivation, learning strategies/preferences, and attitudes towards school. All the within-domain variables had factor loadings higher than .30 in the maximum likelihood PROMAX rotated factor solution. One variable, disciplinary climate, had low communality in the EFA analysis, and thus was excluded from the subsequent CFAs. The highest salient loadings for each domain are from the scales that are postulated to be part of that domain. The motivation factor, however, had additional salient loadings (above .30 but lower than .40) from the cross-over domain variables, i.e., self-concept, competitive learning, and sense of belonging to school. One possible interpretation is that some aspects of motivation are present in these cross-over measures as well. Table 3 presents the correlations among the four second-order factors based on EFA. All correlations among the EFA factors are positive and different from zero; they range between .216 and .552, showing moderate associations.

10.2.2. Confirmatory factor analysis (CFA) results

A series of CFA was carried out to confirm the EFA results and to examine a potential higher-order structure among the noncognitive constructs. First of all, CFA was modeled where the within-domain variables were classified into one of the theoretically-corresponding domains and no cross-over domain variables would load onto that particular domain. (The variable-factor correspondence was described in the introduction section.) Given what was found in EFA, this condition of one-to-one correspondence was a strict condition and, as expected, the CFA fit was neither excellent nor poor (CFI = .900, TLI = .876, RMSEA = .062, SRMR = .055). Our second attempt of CFA utilized the EFA finding that some cross-over variables moderately strongly loaded on the motivation factor. We tested the model where two motivation variables (i.e., interest and instrumental motivation) loaded on all four factors, and the fit of this model was substantially improved (CFI = .941, TLI = .913, RMSEA = .057, SRMR = .051).

10.3. Third-order structure among the fifteen primary scales

We then investigate the existence of a third-order factorial structure. When a single-general factor was modeled to capture the four second-order domain-level variables, we interpret this third-order factor as representing students' noncognitive disposition toward learning in mathematics. Many CFA models were tested, with various combinations of first-, second-, and third-order factors. At the end, we arrived at the third-order model showing a satisfactory goodness-of-fit (CFI = .933, TLI = .909, RMSEA = .058 and SRMR = .053). This third-order model has four second-order factors and one general third-order factor, with the fourteen primary factors at the first-level. Fig. 1 shows this third-order structure of the CFA model (i.e., Fig. 1 minus the mathematics achievement variables and four direct paths leading to it). The CFA column in Table 2 shows the significant loadings (standardized solution) on the second- and third-order factors.

The results of CFA model at the second-order level resemble the results of second-order EFA (presented together in Table 2). The existence of the four major domains is generally supported, with the salient factor loadings of all the first-order factors (minus disciplinary climate) corresponding to their theoretically relevant domains. All freed loadings (i.e., loadings of the cross-domain variables that were set free on the basis of modification indices) were smaller than the factor loadings from the main defining variables for a given factor. Thus, the cross-over loadings did not change the overall interpretation of the major four domain factors. For instance, the factor loading of interest (.258) is smaller than the factor loadings of self-efficacy, self-concept, and anxiety on the self-belief factor.

A few observations about the general third-order factor in this CFA model are as follows. First, it showed moderate to substantial loadings of all four second-order factors (see the last row of Table 2). Second, this third-order noncognitive factor of the hierarchical structure captures relatively little variance of the self-beliefs factor. Although it contributed to the third-order factor, its factor loading (.24) is lower compared to the substantial loadings of the other three factors (above .63). In other words, self-beliefs have relatively little in common with the factors that capture the aspects of the other three domains (i.e., motivation, learning strategies/preferences, and attitude towards school).

Table 3
Correlations among the second-order factors from EFA.

Second-order factors	1	2	3	4
1. Self-beliefs	1.00			
2. Motivation	.468	1.00		
3. Learning strategies	.254	.552	1.00	
4 Attitude towards school	.216	.385	.486	1.00

Table 2
Standardized factor loadings of the second-order EFA and the third-order CFA.

Variables	Domains							
	Self-beliefs		Motivation		Learning strategies/ preferences		Attitudes towards school	
	EFA	CFA	EFA	CFA	EFA	CFA	EFA	CFA
1. Mathematics self-efficacy	.545	.534						
2. Mathematics anxiety	−.843	−.751						
3. Mathematics self-concept	.690	.745	.330	.414				
4. Interest in mathematics		.258	.742	.650				.163
5. Instrumental motivation in mathematics			.489	.580				.258
6. Control strategies					.812	.767		
7. Elaboration strategies				.287	.635	.545		
8. Memorization strategies					.755	.752		
9. Competitive learning			.317	.375	.488	.378		
10. Cooperative learning					.490	.495		
11. Attitudes towards school							.514	.576
12. Student–teacher relations at school							.672	.678
13. Sense of belonging to school			−.338				.438	.357
14. Teacher support in math lessons							.458	.559
15. Disciplinary climate in math class								
Loadings on noncognitive (third-order) factor	–	.243	–	.688	–	.840	–	.636

Note. The CFA factor loadings presented in this table are slightly different from those presented in Fig. 1 because these factor loadings are obtained with absence of the mathematics achievement variables. But the corresponding values in Fig. 1 and Table 2 are very close to each other.

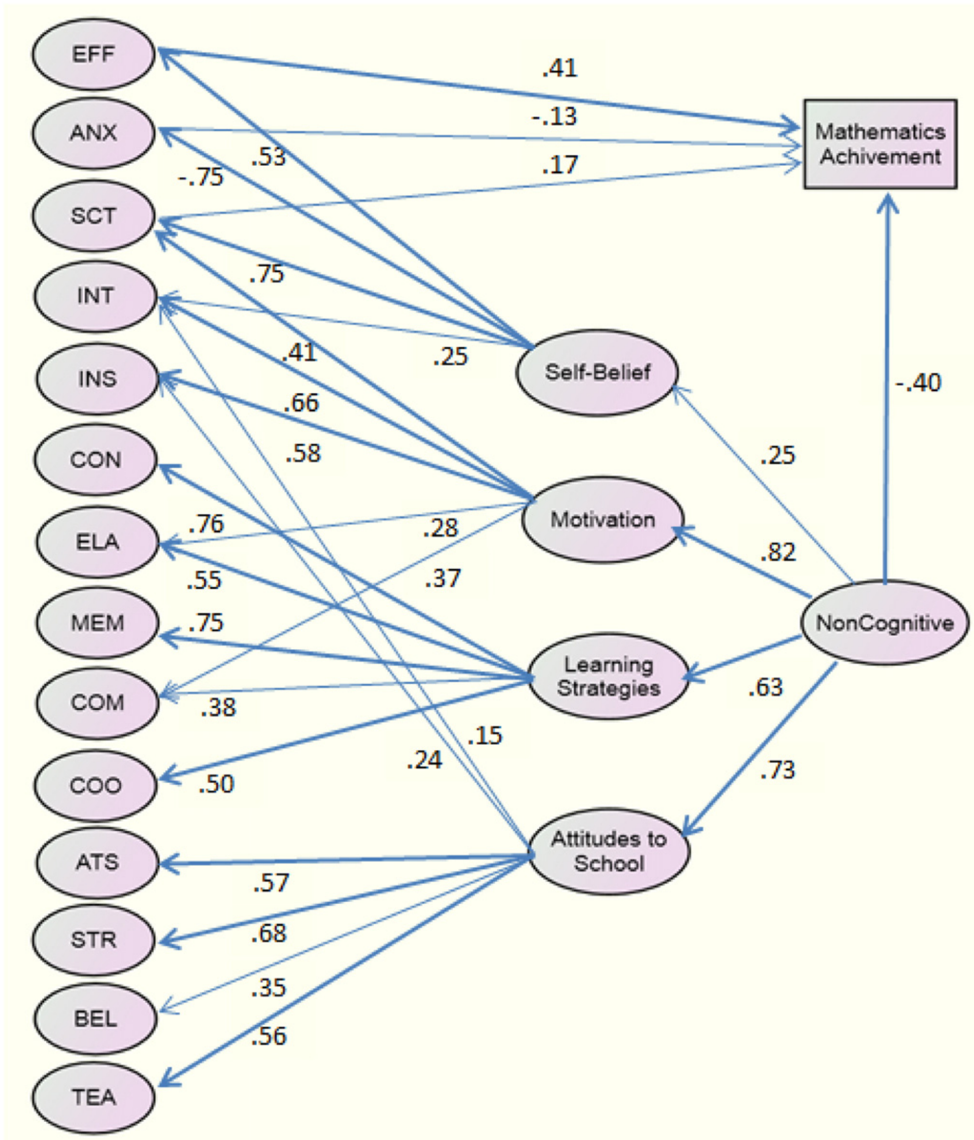

Fig. 1. A structural equation modeling with the fifteen scale and the PISA 2003 mathematics scores. *Note*. EFF: students' self-efficacy in mathematics; ANX: students' anxiety in mathematics; SCT: self-concept in mathematics; INT: interest in and enjoyment of mathematics; INS: instrumental motivation; CON: control strategy; ELA: elaboration strategy; MEM: memorization; COM; competitive learning; COO: cooperative learning; ATS: attitudes towards school; STR: student–teacher relations; BEL: sense of belonging at school; TEA: teacher support. The thicker lines represent the factor coefficients greater than .40.

Third, with the existence of a third-order factor, the CFA model indicated that the motivation factor encompasses some cross-over domain variables and self-concept (with a factor loading of .41) and competitive learning (.38) in particular (see the CFA column in Table 2). It is also interesting that the attitudes toward school factor had significant loadings from two motivation variables – interest in mathematics and intrinsic motivation – even though the loadings are relatively small (.16 and .26, see Table 2).

10.4. Predictive validity of the fifteen primary scales for mathematics achievement

In our attempts to study the relationship between our fifteen primary variables and mathematics performance, we ran several regression analyses. We address two questions: a) How much variance in PISA mathematics achievement can be accounted for by the fifteen primary scales; and b) Given the hierarchical structure outlined above, what constructs within the hierarchy would exhibit predictive validity for mathematics achievement.

10.4.1. Regression with the fifteen primary scales

The last row in Table 1 presents the standardized regression weights of the fifteen primary variables when predicting the PISA 2003 mathematics scores. The multiple correlation coefficient for this solution is $R = .603$ (with $R^2 = .364$). Patterns of correlations with the achievement scores (row 16) and standardized regression weights (last row in Table 1) are similar although there are some differences due to multicollinearity. In particular, the moderate size of associations found with anxiety, and self-concept gets weakened with the presence of other variables in the regression. Thus, out of the three self-beliefs measures, only self-efficacy remains a potent predictor of the mathematic achievement in the presence of the other fourteen predictors. The preponderance of low negative regression weights is as pronounced as is the presence of negative correlations shown in row 16.

It is useful to mention here one other analysis we carried out. In that analysis, we postulated the existence of a single factor directly from the fifteen primary variables, and this general factor was regressed onto the mathematics achievement scores. The outcome was not only poor fit (e.g., CFI = . 611) but also close to zero R^2 value in predicting the mathematics achievement. This illustrates that a) a single general second-order factor in place of the four correlated factors is not viable; and b) predictive validity of a common part of all fifteen variables is negligible.

10.4.2. Regression using the third-order structure

The mathematics achievement scores were added as an outcome/criterion variable onto the third-order factorial structure outlined above (Fig. 1). This structural equation model (SEM) produced satisfactory fit indices (CFI = .933, TLI = .908, RMSEA = .057 and SRMR =.053). The variance of the outcome measure explained by this structure was 38% ($R^2 = 0.38$). The factor loadings in this model are very close to the ones in the previous EFA and CFA results. That is, the coefficients in the CFA portion of this SEM model (i.e., factor loadings on the second- and third-order factors presented in Fig. 1) are very similar to the ones in the second-order EFA and third-order CFA models in Table 2.

Several findings are noteworthy. First, the best model fit was achieved when the regression weight was attached to the self-efficacy construct at the primary level. Additional direct links from self-concept and anxiety to the mathematics scores further improved the fit. This was due to the fact that substantial amount of variance of self-efficacy at the first-order level was not captured by the hierarchical structure. The self-efficacy variable has a lower loading (.53) on its second-order self-beliefs factor than the other two self-beliefs variables do. Furthermore, the second-order self-beliefs factor was not substantially captured by the general, noncognitive factor (its factor loading was only .25). Thus, much of its variance was not accounted for by the structure and remained unique (with residual variance left with 72% at the first-order level).

Second, the regression weight of the third-order, general noncognitive factor on mathematics achievement scores is –.40. That is, small negative weights of the primary variables accumulated to lead to the moderate size of weight at the common third-order level. Thus, the model shows that those students who obtained a higher score on the *common part* of the four domains were on average likely to perform worse on the PISA 2003 mathematics achievement. This result is counterintuitive, and we shall touch upon this issue in the discussion section.

Overall, the final SEM model highlights that the strongest predictors of mathematics achievement are the measures of mathematics self-beliefs and self-efficacy in particular. Even after partialing out the portion of the self-efficacy variance captured by the second-order self-beliefs factor and by the third-order factor, the unique variance of the self-efficacy variable at the first-order level had the strongest predictive power on the mathematics achievement.

11. Discussion

This study examined the higher-order factor structure among the fifteen major constructs from four domains—motivation, self-beliefs, learning strategies, and attitudes toward school. These constructs have been extensively studied (arguably more than any other constructs) in educational psychology. They are known to show good construct validity and strong links to academic/mathematics achievement.

There were several noteworthy findings in this study. First, there was no empirical support for a single general factor directly drawn from the fifteen primary variables. Instead, they were best represented by a third-order model with four factors at the second-order level and one general noncognitive factor at the third-order level. Second, the third-order noncognitive factor had the smallest loading from the self-beliefs factor, suggesting that the self-beliefs construct stands apart from the broad noncognitive factor. Third, the motivation factor has non-trivial loadings from the variables that define the other three domains, meaning that the motivation construct seems to be "present" in the other domains as well. Fourth, in the third-order model, the mathematics achievement was best explained by four significant predictors, three of the self-beliefs measures at the first-order and one third-order noncognitive factor. Last, self-efficacy at the first-order level was the single best predictor of mathematics achievement even though its variance was in part taken away by the shared variance of the other variables at second- and third-order levels.

11.1. A broad noncognitive factor

Within the structure suggested by our findings, it may be possible to postulate the existence of a broad dimension that can be referred to as *Noncognitive Disposition*. What we mean by this is that although each individual variable may have different manifestations (such as learning strategies, motivation, or self-beliefs) and may show particular roles in producing a certain outcome, a single dimension (i.e., noncognitive disposition) can function as an underlying factor across a broad range of psychological and behavioral constructs. This line of thought was expressed in Bowles and Gintis (1976, 2000, 2002), Farkas (2003), Messick (1979), and Lee and Shute (2010) who claimed that the noncognitive dispositions as a whole greatly contribute to one's cognitive development and achievement. The existence of a noncognitive construct can be validated and established further when future studies show that a higher-order factor can emerge across a different set of variables that can be broadly labeled as "noncognitive". Alternatively, the appearance of a single factor at the third-order may be interpreted as an indication of method factor — i.e., people's general tendency to respond to survey questions in a particular way. Surely, this latter hypothesis cannot be validated without additional empirical evidence.

11.2. Special role of self-beliefs

One notable finding of this study is that the mathematics self-belief variables did not load on the common higher-order factor as much as the rest of the constructs did. It was evident in all tested models and at all different factor levels. This is a somewhat surprising result because self-beliefs are often considered to be a strong and adaptive form of motivation (e.g., Bandura, 1997; Clayton et al., 2010; Martin, 2007, 2009; Pajares, 1996; Schunk, 1991). In this light, it was conjectured that the distinctive empirical separation between the two constructs may be hard to achieve. However, the current study shows that they are two clearly separate constructs, suggesting that students with high motivation may not necessarily possess strong self-beliefs and vice versa. This finding has a practical implication that teachers should be mindful about encouraging not only students' motivation but also their self-beliefs in their mathematics aptitude.

11.3. Strong predictive power of self-efficacy

Self-efficacy was the best predictor in relation to the mathematics achievement in this study. This finding was based on the analysis with more than a dozen other predictors that are known to have strong relevance to academic/mathematics achievement. Self-efficacy, after the portion of the shared variance was accounted for by the rest of other variables in the model, showed the strongest predictive power. One interpretation with respect to this predictive validity is that the other frequently studied noncognitive constructs in educational psychology – e.g., motivations, strategies, school climate – could pale into insignificance in comparison to self-beliefs and self-efficacy in particular. Thus, the present study lends strong support to the literature emphasizing the importance of self-beliefs in relation to mathematics achievement (e.g., Bandura, 1986, 1997; Lee, 2009; Oyserman, Bybee, & Terry, 2006; Pajares, 1996; Pajares & Schunk, 2002; Schunk, 1983, 1991; Stankov et al., 2012). This is encouraging in the sense that educators and teachers can implement interventions to promote positive self-beliefs in learning, which is more feasible than some other background variables (e.g., family income). In fact, several recent studies have shown the effectiveness of intervention programs in reducing negative/unbalanced self-concept and self-efficacy and improving academic/mathematics achievement (e.g., Betz & Schifano, 2000; Ginsburg-Block, Rohrbeck, & Fantuzzo, 2006; Oyserman et al., 2006; Portnoi, Guichard, & Lallemand, 2004). The benefits of adaptive and well-balanced self-beliefs go beyond the formal school years (OECD, 2004a). Self-beliefs continue to affect people's lives through their college performance (Pajares & Miller, 1994), their tendency to be resilient (Bandura, 1986), and in pursuit of their own interests and career choices (Lent, Brown, & Hackett, 2000).

The superior link between self-efficacy and mathematics achievement shown in this study may be partly due to task-specificity in the measurement of the self-efficacy construct. As can be seen from the self-efficacy questions in Appendix 1, the self-efficacy items were math- and task-specific in nature. Previous studies have claimed the importance of task-specificity (Bandura, 1997; Pajares, 1996; Stankov & Lee, 2008) and domain-specificity (Marsh, 1986; Marsh et al., 2006; Schunk, 1989; Stankov et al., 2012) in the construct measurement for predicting academic achievement (e.g., asking about math interest to predict mathematics achievement and reading interest to predict reading achievement). The present study shows support for this claim. That is, predictability of mathematics achievement was best when the predictors were measured at the task-level (self-efficacy), followed by the items at the subject-level (self-concept, intrinsic and extrinsic motivation). The constructs measured more generally (i.e., attitude toward school in general) showed the weakest predictive utility.

Another possibility is that the mental activities required to answer the self-efficacy items might have been similar to the actual mathematics problem-solving tasks. The self-efficacy items asked the students about their confidence in solving a specific mathematics task with a concrete example (see Appendix 1). In this sense, cognitive process and demands in answering the mathematics self-efficacy items might have been closely related to the cognitive tasks of solving the actual mathematics items. In addition, answering such task-oriented self-efficacy items would require metacognitive ability (knowing what they know and can do), which has attitudinal as well as cognitive components (Stankov, 1999; Stankov & Lee, 2008). Thus, answering the self-efficacy items would have demanded some level of cognitive activity, which, in turn, might have been related to the strong link between self-efficacy and mathematics achievement.

11.4. Unexpected negative correlation between noncognitive factor and achievement

One unexpected result of this study is that the common variance among learning strategies/preferences and attitude toward school together with motivation and self-beliefs, has a negative correlation with mathematics achievement. We initially postulated that the commonality across our variables would show a positive relationship to our outcome variable. From the theoretical point of view, one variable – anxiety – was expected to show a negative correlation. Review of the literature indicates that additional three variables – memorization, competitive learning and cooperative learning – can also potentially show mixed results when it comes to their relationships to mathematics performance (e.g., see contrasting argument from Cameron et al., 2005; Ginsburg & Bronstein, 1993; Lepper et al., 2005). Correlations between these three variables and mathematics achievement were turned out to be negative in our analyses. Furthermore, in our analyses the correlations of five variables (control, elaboration, attitudes towards school, student–teacher relationships, and teacher support) with achievement are very small (less than .10 except for elaboration) and also negative. Thus, although our fifteen constructs can be combined to form one single general factor at the third-level, each individual variable had a unique relationship to the achievement measure, which could have obscured the directionality of the relationship between the commonality of all fifteen variables and the outcome variable. It was also shown in other studies (e.g., Schwinger et al., 2009) that a negative correlation (although not significant) can emerge between a general motivation factor and student achievement when motivation factor itself consists of many components. Alternatively, this unexpected finding may be due to the heterogeneity of the sample. However, our post-hoc checks revealed that the sign of correlations was largely consistent in the samples of individual countries.

11.5. Limitations of the present study and future research

The findings of this study are based on a large-scale, international database representing 41 countries. This unique, international sample provides the basis for the results to be generalized to the population of students of the same age in 41 countries. This also poses a few challenges, mainly due to the heterogeneous nature of the sample. For instance, although it has been shown that the findings based on the pancultural results tend to be replicated in the multiple-group analysis (see Stankov & Lee, 2009), pancultural results can be of limited use when it comes to generalizability to a single-country setting.

In spite of the rigorous pilot work carried out before the main PISA study, multiple sources of threats to construct validity still exist in the scales when such a large-scale international sample provides the assessment data. Potential threats can originate from various (sometimes unexpected) sources, such as response style, culturally-inherent differences of certain concepts, or some critical contextual and structural features of each country (e.g., education system). It was noted in this study that two school-attitude scales (sense of belonging to school and perceived disciplinary climate) showed particularly weak associations with the achievement scores and in relation to the corresponding higher-order factor. It is possible that this finding could be attributable to weak validity of the two scales, potentially influenced by different cultural contexts. For example, the cultural influences on the responses to the sense of belonging scale (e.g., what constitutes “a sense of belonging”) would probably differ (and be greater) than answering the scales asking about how interesting a given mathematics task is (i.e., interest or intrinsic motivation).

Although the present study included more than a dozen important constructs, there are many other motivational and attitudinal constructs that were left out. Examples include attribution of success/failure (Weiner, 1986), self-discipline (McCann & Turner, 2004), intrinsic values (Pintrich & De Groot, 1990), and emotion regulation (Pekrun et al., 2002; Schutz & Davis, 2000; Schutz & DeCuir, 2002), to name a few. Although the basic structure of our findings may hold, inclusion of additional variables may affect the nature of the higher-order structure or the directionality of the relationship of the higher-order construct to mathematics achievement. Although the difference may be minimal given that academic achievement in various subject areas tends to be highly correlated to each other (cf, OECD, 2004b; Rivkin, Hanusheck, & Kain, 2005), employing subject domains other than mathematics may also provide different findings.

11.6. Concluding remarks

In this study, the higher-order factor model of mathematics achievement was presented with a diverse range of learner characteristics in motivation, self-beliefs, learning strategies, and attitudes toward school. The study was designed with an integrative approach to better understand the factors of students' mathematics outcomes from motivational, behavioral, metacognitive, social-cognitive, and affective domains. Although recent research attempts to integrate a wide range of psycho-educational constructs (e.g., Lee & Shute, 2010; Marsh et al., 2006; Martin, 2007, 2009), there is still a need for more empirical research directed at incorporating diverse learning-outcome models into one unifying framework, as we presented in this study. We hope that future studies will be carried out to validate a construct that we labeled ‘noncognitive disposition’ in this study. Furthermore, its validation in different subject domains will strengthen our supposition of its existence as a unifying construct encompassing a broad range of education-related psychological dispositions.

Appendix 1. PISA (2003) constructs and items used in the present study

Construct	Items	Reliability
Self-beliefs		
Students' self-efficacy in mathematics (MATHEFF): The extent to which students believe that they can do the task being asked (Bandura, 1986).	1. Using a train timetable to work out how long it would take to get from one place to another. (+) 2. Calculating how much cheaper a TV would be after a 30% discount. (+) 3. Calculating how many square meters of tiles you need to cover a floor. (+) 4. Understanding graphs presented in newspapers. (+) 5. Solving an equation like $3x + 5 = 17$. (+) 6. Finding the actual distance between two places on a map with a 1:10,000 scale. (+) 7. Solving an equation like $2(x + 3) = (x + 3)(x - 3)$. (+) 8. Calculating the petrol consumption rate of a car. (+)	.82
Students' anxiety in mathematics (ANXMAT): The extent to which student feel helpless or stressed (Meece, Wigfield, & Eccles, 1990).	1. I often worry that it will be difficult for me in mathematics classes. (−) 2. I get very tense when I have to do mathematics homework. (−) 3. I get very nervous doing mathematics problems. (−) 4. I feel helpless when doing a mathematics problem. (−) 5. I worry that I will get poor marks in mathematics. (−)	.82
Self-concept in mathematics (SCMAT): The extent to which students feel competent in the domain being asked (Harter, 1985a, 1985b; Marsh, 1986, 2007).	1. I am just not good at mathematics. (−) 2. I get good marks in mathematics. (+) 3. I learn mathematics quickly. (+) 4. I have always believed that mathematics is one of my best subjects. (+) 5. In my mathematics class, I understand even the most difficult work. (+)	.89
Motivation		
Interest in and enjoyment of mathematics (INTMAT): The intensity and continuity of engagement and enjoyment in mathematics (OECD, 2004a, 2004b).	1. I enjoy reading about mathematics (+) 2. I look forward to my mathematics lessons. (+) 3. I do mathematics because I enjoy it. (+) 4. I am interested in the things I learn in mathematics (+)	.90
Instrumental motivation (INSTMOT): The extent to which students make an effort to learn for external rewards (Deci & Ryan, 1992).	1. Making an effort in mathematics is worth it because it will help me in the work that I want to do later. (+) 2. Learning mathematics is important because it will help me with the subjects that I want to study further on in school. (+) 3. Mathematics is an important subject for me because I need it for what I want to study later on. (+) 4. I will learn many things in mathematics that will help me get a job. (+)	.87
Learning strategies and preference		
Control (CSTRAT): The extent to which students regulate learning by planning, monitoring, and evaluating (Pokay & Blumenfeld, 1990).	1. When I study for a mathematics test, I try to work out what are the most important parts to learn. (+) 2. When I study mathematics, I make myself check to see if I remember the work I have already done. (+) 3. When I study mathematics, I try to figure out which concepts I still have not understood properly. (+) 4. When I cannot understand something in mathematics, I always search for more information to clarify the problem. (+) 5. When I study mathematics, I start by working out exactly what I need to learn. (+)	.72
Elaboration (ELAB): Students' ability to connect their knowledge to other contexts (Pintrich & De Groot, 1990).	1. When I am solving mathematics problems, I often think of new ways to get the answer. (+) 2. I think how the mathematics I have learned can be used in everyday life. (+) 3. I try to understand new concepts in mathematics by relating them to things I already know. (+) 4. When I am solving a mathematics problem, I often think about how the solution might be applied to other interesting questions. (+) 5. When learning mathematics, I try to relate the work to things I have learnt in other subjects. (+)	.73
Memorization (MEMOR); The extent to which students store knowledge without processing (OECD, 2004a, 2004b).	1. I go over some problems in mathematics so often that I FEEL AS IF I could solve them in my sleep. (+) 2. When I study mathematics, I try to learn the answers to problems off by heart. (+) 3. In order to remember the method for solving a mathematics problem, I go through examples again and again. (+) 4. To learn mathematics, I try to remember every step in a procedure. (+)	.60
Competitive learning (COMPLRN): The extent to which students' motivation to learn is rooted in their desire to do better than others (see Johnson & Johnson, 1989).	1. I would like to be the best in my class in Mathematics. (+) 2. I try very hard in Mathematics because I want to do better in the exams than the others. (+) 3. I make a real effort in Mathematics because I want to be one of the best. (+) 4. In Mathematics I always try to do better than the other students in my class. (+) 5. I do my best work in Mathematics when I try to do better than others. (+)	.84
Cooperative learning (COOPLRN): To the extent that students can make an effort, learn and enjoy working with other students (see Slavin, 1980, 1996).	1. In Mathematics I enjoy working with other students in groups. (+) 2. When we work on a project in Mathematics, I think that it is a good idea to combine the ideas of all the students in a group. (+) 3. I do my best work in Mathematics when I work with other students. (+) 4. In Mathematics, I enjoy helping others to work well in a group. (+) 5. In Mathematics, I learn most when I work with other students in my class. (+)	.77
Attitudes toward school		
Teacher support (TEACHSUP): The extent to which students feel that teachers show respect and interest in them (Wentzel, 1994).	1. The teacher shows an interest in every student's learning. (+) 2. The teacher gives extra help when students need it. (+) 3. The teacher helps students with their learning. (+) 4. The teacher continues teaching until the students understand. (+) 5. The teacher gives students an opportunity to express opinions. (+)	.83

Appendix 1 (*continued*)

Construct	Items	Reliability
Student–teacher relations (STUREL): The extent to which students feel about their teachers' behaviors towards them (Wentzel, 1994).	1. Students get along well with most teachers. (+) 2. Most teachers are interested in students' well-being. (+) 3. Most of my teachers really listen to what I have to say. (+) 4. If I need extra help, I will receive it from my teachers. (+) 5. Most of my teachers treat me fairly. (+)	.76
Disciplinary climate (DISCLIM): The extent to which students perceive orderliness and control in the classroom (Ames, 1992).	1. Students don't listen to what the teacher says. (−) 2. There is noise and disorder. (−) 3. The teacher has to wait a long time for students to quiet down. (−) 4. Students cannot work well. (−) 5. Students don't start working for a long time after the lesson begins. (−)	.83
Attitudes towards school (ATSCHL): The extent to which students think positive or negative about their school experience (Elliot & Dweck, 2005).	1. School has done little to prepare me for adult life when I leave school. (−) 2. School has been a waste of time. (−) 3. School helped give me confidence to make decisions. (+) 4. School has taught me things which could be useful in a job. (+)	.58
Sense of belonging at school (BELONG): The extent to which students feel like an outsider or awkward or lonely in the school (Finn, 1989).	1. I feel like an outsider (left out of things). (−) 2. I make friends easily. (+) 3. I feel like I belong. (+) 4. I feel awkward and out of place. (−) 5. Other students seem to like me. (+) 6. I feel lonely. (−)	.74

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