Achievement Goal Profiles Among Adolescent Males and Females

David Litalien[a], Alexandre J. S. Morin[b], and Dennis M. McInerney[c]

[a] Department of Educational Fundamentals and Practices,Université Laval, Canada

[b] Department of Psychology, Concordia University, Canada

[c] Department of Special Education and Counselling, The Education University of Hong Kong, Hong Kong

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Correspondence concerning this article should be addressed to David Litalien, 2320, rue des Bibliothèques, Office 974, Université Laval, Québec (Québec), G1V 0A6, Canada. E-mail: David.Litalien@fse.ulaval.ca

Abstract

Achievement goal theory has long been a dominant model in the study of student motivation. However, a relatively small number of researchers have investigated gender differences in achievement goals, or have considered the possible role that social and extrinsic goals may play in student academic motivation. Adopting a person-centered multiple goals perspective based on Personal Investment Theory, this longitudinal study investigated whether males and females shared similar goal profiles, and whether the predictors (facilitating conditions) and outcomes (learning processes, task perseverance, and future aspirations) of these profiles were equivalent across genders. Profiles were extracted from eight types of academic goals, based on a large sample of Hong Kong high school students (N = 7,848). Findings revealed five distinctive profiles for both males and females. Although the relative size of these profiles differed across samples of male and female students, the results show that four of these profiles were mostly equivalent across genders. Predictors of membership into these profiles were also equivalent across genders, whereas their relative outcomes were specific to gender.

Keywords: achievement goal profiles, gender differences, Personal Investment Theory, latent profile analyses, gender invariance

Academic motivation is one of the key determinants of students' achievement, effort, educational and vocational choices, interest, and persistence (Covington, 2000; Wigfield, Cambria, & Eccles, 2012). Achievement goals, which describe the purposes or reasons underlying achievement-related behaviors, represent one of the key constructs through which academic motivation has been studied (Maehr & Zusho, 2009; Pintrich, 2003). Although these goals represent important determinants of desirable academic outcomes (Covington, 2000), many questions remain to better understand the mechanisms underlying the effects of these goals. For instance, researchers have recognized that individual students can simultaneously endorse a variety of achievement goals (Dowson & McInerney, 2003; Pintrich, 2000) and suggest that such goal combinations may yield more positive outcomes than their isolated adoption (Barron & Harackiewicz, 2001). However, little is known on how the full range of achievement goals (e.g., McInerney & Ali, 2006) can be combined, how these combinations emerge, and the exact role they play in the determination of students' outcomes.

A person-centered approach allowing for the identification of profiles of students presenting a distinct configuration of achievement goals may prove useful to unpack the combined effects of achievement goals on desirable outcomes in a more holistic manner (Linnenbrink-Garcia et al., 2012). A key advantage of this approach for developmental research is the ability to study the predictors or consequences of distinct configurations of achievement goals, rather than to study each specific type of achievement goal in isolation or through the inclusion of a limited number of interactions, as it is typically the case in variable-centered studies (Morin, Morizot, Boudrias, & Madore, 2011). Allowing the investigation of potential cumulative effects of multiple goals endorsement over time, this approach is well-suited to the study of individual development (Magnusson, 1998; Pintrich, 2000).

Importantly, the adoption of specific configurations of achievement goals, as well as their relations with predictors or outcomes, may differ according to gender-differentiated processes (Hyde & Durick, 2006; Meece & Painter, 2012). This could be particularly true during the developmental period of adolescence, which is accompanied by an intensification of gender-differentiated socialization processes (Hill & Lynch, 1983). However, very little research has explored gender differences in regards to achievement goals combinations, as well as their predictors and outcomes. For instance, no study has yet investigated the structure of those combinations separately for male and female students and their degree of similarity across genders. Adopting a multiple goals perspective, this study aims to explore the extent to which achievement goal profiles, as well as their relations with key predictors and outcomes, generalize across genders in a sample of Hong Kong adolescents.

Personal Investment Theory

From its inception, Personal Investment Theory (PIT) has highlighted the need to consider the full range of achievement goals that might influence students' academic choices and behaviors in order to adequately capture individual differences as they occur in a variety of academic and cross-cultural contexts (Maehr, 1984; Maehr & McInerney, 2004; Zusho & Clayton, 2011). PIT is "concerned with how people choose to invest their energy, talent, and time in particular activities" (Maehr & McInerney, 2004, p. 73). This theoretical framework predates achievement goal theory and includes a focus on social and extrinsic goals, in addition to the more commonly considered mastery and performance goals. Social goals emerge from social concerns that are known to be particularly important for children and adolescents (Ladd, Herald-Brown, & Kochel, 2009; Urdan, 1997), especially within schools that are inherently social environments (Lee, McInerney, Liem, & Ortiga, 2010). In addition, the pursuit of external rewards for achievement could be more common than the competitive desire to outperform others (e.g., Brophy, 2005).

PIT proposes that each of these four types of goals is universal and incorporates two facets, forming a multidimensional approach including eight distinct goal facets (McInerney & Ali, 2006; McInerney, 2012). Mastery Goals encompass Task Involvement (i.e., being interested in schoolwork and in improving one's competence) and Effort (i.e., readiness to try hard and persist to improve one's competence through schoolwork). Performance Goals incorporate Competition (i.e., desire to do better than others at schoolwork) and Social Power (i.e., desire to perform socially, to achieve

social power and leadership, through schoolwork). Social Goals[1] include Affiliation (i.e., seeking opportunities to collaborate with other students at schoolwork) and Social Concern (i.e., being concerned for other students, seeking to help others students in the context of schoolwork). Finally, Extrinsic Goals cover Praise (i.e., seeking social recognition, praise, and approval for one's schoolwork) and Token Reward (i.e., seeking tangible rewards for schoolwork, such as certificates and prizes). According to PIT, gender differences are likely to be expressed in the specific achievement-related activities in which people decide to invest their efforts, as well as in the reasons underlying these decisions. PIT has led to the development of a companion measure of these eight goals, the Inventory of School Motivation (ISM; McInerney & Ali, 2006). Psychometric research on the ISM has provided strong support for its a priori multidimensional structure across genders (King & Watkins, 2013) and cultural groups (e.g., students from Hong Kong, Philippines, Australia [Aboriginal or European background]) (Ganotice, Bernardo, & King, 2012; King & Watkins, 2013; McInerney, 2012), making this instrument particularly well-suited to the present study.

A Holistic Multiple Goal Perspective. In line with PIT, research has generally supported the importance of recognizing that students can simultaneously endorse a variety of goals (Dowson & McInerney, 2003; Pintrich, 2000; Senko, Hulleman, & Harackiewicz, 2011). For instance, some studies have shown that the combined endorsement of mastery and performance goals might yield more positive outcomes than their isolated adoption (e.g., Barron & Harackiewicz, 2001). These observations led Pintrich (2003) to suggest that research needed to move beyond simplistic unidimensional approaches to focus on the simultaneous operation of multiple goals within students, and on understanding how each specific goal may create a context for the other goals. Thus, on their own, performance goals may express a competitive desire to outperform others, whereas in association with mastery goals, they may reflect a desire to demonstrate mastery of a school subject. Alternatively, combined with social goals, they may reflect a desire to work collaboratively to increase performance within peer groups that value academic performance. A person-centered approach allowing for the identification of relatively homogeneous subgroups of participants presenting qualitatively and quantitatively distinct configurations of achievement goals (Morin & Marsh, 2015) represent a promising way to refine this holistic understanding of how achievement goals operate in combination (Linnenbrink-Garcia et al., 2012). Although the variable-centered investigation of interaction effects could also help to improve knowledge regarding the combined effects of goals, it is almost impossible to interpret interaction effects involving more than three variables, whereas no limit exists for profiles.

Previous research on multiple goals has generally been limited to the classical distinction between mastery and performance goals. This research has relied on a variety of methodological approaches including interaction effects (Barron & Harackiewicz, 2001), the comparison of arbitrary groups formed through a midpoint-split approach (Bouffard, Boisvert, Vezeau, & Larouche, 1995; Pintrich, 2000), and true person-centered analyses including cluster analyses (Daniels et al., 2008; Meece & Holt, 1993) and latent profile analyses (LPA; Luo, Paris, Hogan, & Luo, 2011; Pastor, Barron, Miller, & Davis, 2007; Tuominen-Soini, Salmela-Aro, & Niemivirta, 2012). These studies, conducted among samples of adolescents or university students from the United States, Canada, Singapore or Finland, have shown that mastery-oriented students tend to display more favorable academic outcomes, whereas students reporting a low level of both goals show the least adaptive academic outcomes. Results are less consistent for the combination of mastery and performance goals, showing that it

[1] According to PIT, social goals refer to "*perceived social purposes for trying, or not trying, to achieve academically*" (Urdan & Maehr, 1995, p. 214). This conceptualization is adopted in the present study and other ISM-based research. However, other studies have adopted a different approach to social goals. First, Wentzel (1993, 1997, 2003) subdivides social goals into prosocial and social responsibility goals. Prosocial goals are similar to social concern goals assessed via the ISM and refer to sharing with peers and helping them with academic problems, whereas social responsibility goals refer to keeping commitment to peers and following classroom rules – an aspect not directly covered in the ISM. Second, Shim and Finch (2014) and Ryan and Shim (2008) operationalized social goals as the development or demonstration of social competence. These types of social goals are related to the general social domain rather than to the achievement domain per se.

predicts better, similar, or worse academic outcomes than the pure pursuit of mastery goals.

Only limited research has looked at combinations of multiple goals including social or extrinsic goals. Wentzel (1993) contrasted groups of sixth- and seventh-grade American students identified through a midpoint-split approach based on the degree to which they focused on social relationships or academic (a mastery and performance composite) goals. Her results showed that combining high social and academic goals was related to the highest levels of achievement, while combining high social and low academic goals was related to higher levels of academic achievement than combining low social and low academic goals. Finally, achievement levels observed for the high academic and low social goals combination did not significantly differ from those observed for the low social and low academic goals. In a midpoint-split study of performance, mastery, and social goals endorsed by Hong Kong adolescents, Watkins and Hattie (2012) found the highest achievement levels among students who adopted high mastery, high performance, and low social goals, as well as among those who endorsed high social and low mastery goals (regardless of performance goals). Students presenting high mastery, low performance, and high social goals showed the second-lowest achievement scores. In total, a third of the students presented low levels on all three goals, whereas one fifth presented high levels on all three goals. The midpoint-split approach used in these two studies represents a key limitation, as this approach may fail to detect meaningful subpopulations, or force the extraction of subgroups that do not exist naturally (Morin, Morizot, et al., 2011).

In contrast to the midpoint-split approach, cluster analyses and LPA do not create artificial subgroups. In addition, LPA has several advantages over cluster analyses (e.g., providing various indices for comparison, integration of covariates; for details see Morin & Wang, 2016). More importantly, in relation to the present investigation, LPA provides a way to systematically and quantitatively contrast person-centered solutions across meaningful subgroups of participants (Morin, Meyer, Creusier, & Biétry, 2016). In one of the few true person-centered LPA studies focusing on mastery, performance and social goals, Shim and Finch (2014) identified six profiles of American adolescents, corresponding to three distinct patterns: (a and b) high levels of mastery and social goals; (c and d) moderate levels on all goals; (e and f) low levels on all goals. Within each pattern, the key difference between pairs of profiles is that one profile (b, d, and f) always presented higher levels of social goals, or more diverse social goals, than the other (a, c, e). The highest level of school adjustment (engagement, help seeking behaviors, adaptive learning strategies, and academic beliefs) was associated with the mastery-oriented profiles (a, b). The moderate profile with higher social goals (d) presented higher levels of school and social adjustment than the remaining profiles, while the low profile with higher social goals (f) did not differ from the other low profile (e). The authors concluded that social goals may help students with modest academic goals to stay engaged.

In a more recent LPA study of adolescents from the Netherlands focusing on the four broad types of ISM goals (i.e., mastery, performance, social, and extrinsic), Korpershoek, Kuyper, and van der Werf (2015) identified six profiles, again corresponding to fewer patterns: (a) a high level of performance and extrinsic goals; (b) a high level of mastery and social goals, (c) a high level on all goals; (d, e, and f) a low level on all goals, but extremely low levels of performance and extrinsic goals for profiles (e) and (f). School commitment and academic self-efficacy were found to be highest in profiles presenting high levels of achievement goals, and lowest in profiles characterized by lower than average levels of achievement goals. However, all profiles showed similar levels of academic achievement. These patterns were replicated across four educational tracks, although students in the lowest tracks were overrepresented in the profiles characterized by lower levels of achievement goals.

On the one hand, these studies support the value of considering achievement goals configurations in the prediction of educational outcomes. On the other hand, no study has yet considered the full array of eight achievement goal facets proposed by PIT. In addition, conclusions regarding the nature of these combinations from LPA studies remain unclear and hard to integrate given that both studies focused on a different set of goals operationalized differently. Finally, none of these studies addressed gender differences in goals combination and their associations with predictors and outcomes.

Gender and Achievement Goals

Gender differences in achievement goals are more inconsistent (Hyde & Durik, 2005) and further

work is needed to better identify gender similarities or differences both in terms of goal endorsement and on the relations between goals, predictors, and outcomes (Hulleman & Senko, 2010; Meece & Painter, 2012). In particular, the possibility of gender-differentiated developmental processes in terms of achievement goal configurations, and relations between these configurations and a series of predictors and outcomes appears to be particularly important to consider during adolescence. Adolescence tends to be accompanied by an intensification of gender-differentiated socialization processes and demands for gender-role conformity, which become more salient with puberty (e.g., Hill & Lynch, 1983). For this reason, gendered-differentiated interests and activities appear particularly salient during this development period (Ruble, Martin, & Berenbaum, 2006).

In the school context, although gender differences in academic abilities seem negligible, such differences are far more likely to be present when considering self-regulation concepts such as goals, motivation, or expectancies (Meece & Painter, 2012). For instance, gender may influence students' social interactions, which can subsequently affect motivational processes (Hyde & Durik, 2006). Gender differences on these concepts are not trivial, as they can affect achievement, academic pathways, career choices, and even vocational outcomes (Meece & Painter, 2012), which are likely to have significant implications in later life (Eccles, Templeton, Barber, & Stone, 2003).

A well-documented gender difference is that females tend to focus on interdependence, whereas males tend to focus on independence (Cross & Madson, 1997; Helgeson, 1994). Socialization has a major role to play in this specific differentiation and students' goals could be affected by those tendencies (Cross & Madson, 1997). For instance, these tendencies could affect competition, affiliation, and social concerns goals. Parental practices could influence students to adopt certain types of goals in function of their gender (Kenney-Benson, Pomerantz, Ryan, and Patrick, 2004). As an example, Yee and Eccles (1988) found that parents attributed success in math to talent for males and to effort for females, which could affect the endorsement of mastery goals.

Previous Research on Gender Differences in Goal Endorsement. In previous research based on the classical mastery/performance distinction, results generally showed that female students were more likely than males to pursue mastery goals (Elliot & McGregor, 2001; Gherasim, Butnaru, & Mairean, 2012; McInerney, Hinkley, Dowson, & Van Etten, 1998; Nie & Liem, 2013). These results further showed these differences to be consistent across cultures (e.g., Americans, Romanians, Anglo and Aboriginal Australians, Chinese) and developmental level (adolescents and young adults). This difference generalizes to the science domain, a stereotypically male discipline (Anderman & Young, 1994), although some studies report higher levels of mastery goals in science among low ability males students (Meece & Jones, 1996), or no differences at all (Greene & DeBacker, 1999; for a review see Hyde & Durik, 2005). Results are even more inconsistent for performance goals, showing higher levels among males (Anderman & Young, 1994; Linnenbrink, Ryan, & Pintrich, 1999; McInerney et al., 1998) or females (Bouffard et al., 1995; Harackiewicz et al., 1997; Wentzel, 1993).

Less research has been conducted on social or extrinsic goals, again with inconclusive results. McInerney et al. (1998) did not find gender differences on social goals level among Australian adolescents from different cultural backgrounds. Investigating five types of social goals among Filipino adolescents, King et al. (2012) results showed gender differences on most goals, with females being more likely than males to pursue social responsibility, social concern, and social status goals, and males being more likely to pursue social affiliation goals. Studies using other theoretical frameworks than PIT to operationalize social goals also supported these results, suggesting that females were more likely to endorse social responsibility goals and friendship goals, whereas males endorsed more social status goals (Patrick, Hicks, & Ryan, 1997; Wentzel, 1993; Wentzel, Filisetti, & Looney, 2007). Regarding extrinsic goals, Midgley and Urdan (1995) found that male adolescents were more likely than their female counterparts to endorse such goals, whereas Urdan (1997) found the opposite, and no differences were reported by Kasser and Ryan (1996) among young adults. Finally, King and Ganotice (2014) found that Filipino adolescent females scored higher than males on social, extrinsic, and mastery goals, but not on performance goals (also see King & Watkins, 2013).

Goal Profiles. Although gender differences on specific goals endorsement have been found in variable-centered studies, it remains unclear how these differences translate to a person-centered

perspective. As mentioned above, females generally tend to present higher levels of mastery and social goals relative to males. These differences could be reflected in profiles in different ways. On the one hand, gender-specific profiles may be observed, such as profiles characterized by higher levels of mastery and social goals which may be specific to female students. On the other hand, the structure of the profiles could be equivalent across genders, but females might be more frequently represented in profiles characterized by higher level on these specific goals relative to males.

To our knowledge, no study has yet extracted achievement goal profiles independently for male and female students, making it impossible to clearly ascertain whether the nature of the profiles can differ across genders. To date, person-centered studies have simply contrasted the relative frequency of male and female students in profiles extracted while only considering mastery and performance goals. Once again, the results from these studies tend to be highly inconsistent, possibly due to the reliance on suboptimal mid-point splits strategies and the consideration of a limited number of goals. For instance, Bouffard et al. (1995) found that the proportion of late adolescent female students was significantly higher in the high-mastery/high-performance profile, whereas males were more numerous than females in low-mastery/low-performance profile. No gender differences were observed for the profiles with a dominant type of goal (either high-mastery/low-performance or low-mastery/high performance). Among fifth- and sixth graders, Meece and Holt (1993) also observed a male dominance in low-mastery/low-performance group, but found a greater proportion of females in the high-mastery/low-performance group. In contrast, Levy-Tossman, Kaplan, and Assor (2007) found a greater proportion of Israeli male adolescents in the high performance profile, a greater proportion of females in the low performance profile, but no gender differences in the high-mastery/high-performance profile.

Goal Outcomes and Predictors. Very little research has looked at possible gender-differentiated patterns of associations between predictors and achievement goals, and between achievement goals and educational outcomes (Covington, 2000; Hyde & Durik, 2005). In fact, gender is more commonly assessed as a predictor of achievement goals than as a moderator of their associations with a variety of covariates, when it is not simply treated as a control variable (e.g., Hulleman, Durik, Schweigert, & Harackiewicz, 2008). Still, a more refined understanding of gender as a determinant of the nature of achievement goals profiles, and of the relations between these profiles and a variety of predictors and outcomes, appears critical to the design of motivational interventions sensitive to differences in boys and girls educational pathways. For instance, some studies showed that performance goals are especially beneficial for males in regard to the use of metacognitive strategies, motivation, work memory, and affiliation with peers who value education (Bouffard et al., 1995; Linnenbrink et al., 1999; Urdan, 1997). Research also suggested that performance goals tended to be associated with greater levels of academic performance for both males and females (Bouffard et al., 1995; Harackiewicz, Barron, Tauer, & Elliot, 2002), while another study found that they only predicted mathematic achievement for adolescent females (Gherasim et al., 2012). In contrast, mastery goals predicted more desirable academic outcomes for both males and females (Bouffard et al., 1995). In terms of predictors, we only found two studies investigating gender differences. Results suggest that incremental and fixed views of ability (Chen & Pajares, 2010) and individual- and social-oriented achievement motives (Nie & Liem, 2013) predicted achievement goals similarly across genders.

Thus, preliminary research evidence, at least regarding achievement goals outcomes, suggests that gender-differentiated pathways could explain the inconsistent results obtained in certain studies (Hyde & Durik, 2005; Midgley, Kaplan, & Middleton, 2001). Social goals are clearly one area where gender differences can be expected (e.g., independence vs. interdependence). However, so far a single study has looked at gender differences in this area, and has revealed similar relations between social competence goals and students' social adjustment for both males and females (Ryan & Shim, 2008).

The Present Study

The purpose of this study is to investigate whether male and female students share similar goal configurations (based on the eight goals dimensions covered in the ISM), and whether the predictors and outcomes of these configurations are similar across genders. In a first step, we extracted latent profiles separately for each gender. Although we consider a greater number of goals in the current

study, based on the results from previous LPA studies, we also expected to find around six profiles (Korpershoek et al., 2015; Shim & Finch, 2014).

Second, we investigated the degree to which the profiles would be replicated across genders, using a new methodology designed to assess the similarity of latent profiles across groups (Morin, 2016; Morin & Wang, 2016). As previous research only compared the relative frequency of males and females in profiles extracted from a total sample, our approach remains exploratory. Still, based on previous studies, we expected females to be more frequent in profiles relatively high in mastery or social goals, and males to be frequent in profiles relatively high in performance and extrinsic goals.

Third, we extend previous research by considering educational outcomes of achievement goals profiles, predictors of profile membership, and the extent to which relations with these predictors and outcomes generalize across genders. To support the idea that profiles reflect substantively important subgroups, it is critical to follow a systematic process of construct validation aimed at demonstrating that the profiles have heuristic and theoretical value and meaningfully relate to outcomes and predictors (Marsh, Lüdtke, Trautwein, & Morin, 2009; Morin, Morizot, et al., 2011; Muthén, 2003).

Outcomes. Achievement goals have been repeatedly found to predict important educational outcomes. For instance, learning processes have commonly been studied as potentially important outcomes of achievement goals in variable-centered studies, which have generally reported positive relations between: (a) mastery and social goals and the adoption of deep learning strategies (Elliot & McGregor, 2001; King, McInerney, & Watkins, 2010, 2013; Watkins & Hattie, 2012); (b) performance goals and the adoption of superficial (Hulleman, Schrager, Bodmann, & Harackiewicz, 2010) and deep (Watkins & Hattie, 2012) learning strategies. In a person-centered study, Dela Rosa and Bernardo (2013) found that adolescents who endorsed both mastery and performance goals reported a greater use of deep learning strategies. Task perseverance is also a relevant educational outcome to consider (Barron & Harackiewicz, 2001), and research has shown that it tended to be positively related to both mastery and performance goals (Elliot, McGregor, & Gable, 1999). In physical education settings, Guan, Xiang, Ron, and April (2006) found that social responsibility goals more strongly predicted persistence than mastery or performance goals. Another potentially crucial outcome of academic goals, especially when considered from a multidimensional perspective, is students' future aspirations. From a developmental perspective, future aspirations are particularly important to consider, as they are known to predict educational attainment (Beal & Crockett, 2010). Lee et al.(2010) suggested that future aspirations can emerge from academic and learning activities, and that encouraging both mastery and performance goals could enhance various life-ambitions. They found that intrinsic future aspirations (career, family, society) were more strongly related to mastery goals, while extrinsic future aspirations (fame and wealth) were more strongly related to performance goals. To a weaker extent, performance goals positively predicted intrinsic future aspirations, whereas mastery goals negatively predicted extrinsic future aspirations. As future aspirations processes and their perceived importance can vary across genders (Greene & DeBacker, 2004; Kasser & Ryan, 1996), achievement goal profiles may also have different consequences across genders.

Predictors. The environment can have a substantial impact on motivational processes (Maehr & Zusho, 2009). For instance, factors such as the perceived quality of interactions with peers, parents, and teachers, as well as school-related interest, valuing and affect have been proposed to play a key role in shaping achievement goals (McInerney, Dowson, & Yeung, 2005). Wentzel found that perceived teacher support positively predicted the pursuit of prosocial and social responsibility goals (Wentzel, 1997), whereas peer rejection negatively predicted prosocial goals (Wentzel, 2003). Ciani, Sheldon, Hilpert, and Easter (2011) also found that perceiving teachers as controlling decreased mastery goals adoption while perceiving them as supportive had the opposite effect. Similarly, Urdan (1997) showed that affiliating with peers who did not value education negatively predicted mastery goals adoption. Harackiewicz, Durik, Barron, Linnenbrink-Garcia, and Tauer (2008) revealed reciprocal effects between interest and mastery goals adoption in a longitudinal study of college students. A key issue that has yet to be investigated is the extent to which the effects of these facilitating conditions will generalize across genders and how these predictive relations involving individual goals will be transformed when considered from a multidimensional perspective.

Method

Participants and Procedures

A total of 7,848 Hong Kong students from 16 high schools participated in a two-year longitudinal study conducted between 2010 and 2011 (M_{age} = 13.3 years, *SD* = 1.1, 53.8% males; gender was self-reported by the students). Each year, participants were invited to complete, during usual school periods, a 35-minute paper questionnaire targeting achievement goals and learning strategies. Most of the participants reported Cantonese as their main language (91.1%), while the remaining mentioned Mandarin, English, or others. Parents' highest educational level was mostly high school (junior or senior, 68%). At Time 1, 32.0%, 33.3% and 34.7% were respectively enrolled in Secondary 2 (Year 8), 3 (Year 9), and 4 (Year 10). 7,174 students provided Time 2 data regarding the outcomes (8.6% attrition). These students did not significantly differ from those who dropped out on Time 1 measures.

Measures

Achievement goals (Time 1). The ISM (McInerney & Ali, 2006) was used to assess the eight dimensions of achievement goals proposed by PIT: (a) Task (4 items, α = .782; e.g., "I like to see that I am improving in my schoolwork"); (b) Effort (7 items, α = .864; e.g., "I work hard to try to understand new things at school"); (c) Competition (6 items, α = .857; e.g., "I like to compete with others at school"); (d) Social Power (6 items, α = .881; e.g., "It is very important for me to be a group leader"); (e) Affiliation (3 items, α = .693; e.g., "I try to work with friends as much as possible at school"); (f) Social Concerns (4 items, α = .828; e.g., "It is very important for students to help each other at school"); (g) Praise (5 items, α = .902; e.g., "Praise from my teachers for my good schoolwork is important to me"); (h) Token Reward (5 items, α = .890; e.g., "I work best in class when I can get some kind of reward"). Participants were asked to rate each item using a four-point Likert scale (1 = *strongly disagree*, 4 = *strongly agree*).

Outcomes (Time 2). Potential outcomes were measured at Time 2. First, the Future Goals Questionnaire (FGQ; Lee et al., 2010) was used to assess students' future aspirations in the following areas: Fame (3 items, α = .918; e.g., "I want to become a famous person in my society"), career (3 items, α = .912; e.g., "I want to get a good work position"), wealth (3 items, α = .877; e.g., "I want to make a lot of money"), family (3 items, α = .914; e.g., "I want to support my future family"), and society (3 items, α = .857; e.g., "I want to make a contribution to my society"). Second, deep (5 items, α = .836; e.g., "When I study, I relate new knowledge to my prior knowledge") and surface (5 items, α = .667; e.g., "I tend to study only the scope of examination, and don't study anything extra") learning were assessed using the Learning Process Questionnaire (LPQ; Biggs, 1987; McInerney, Cheng, Mok, & Lam, 2012). Third, five items were used to assess task perseverance (α = .857; e.g., "I do not stop my work even if it is very difficult). Participants were asked to rate every outcome-related item using a four-point Likert scale (1 = *strongly disagree*, 4 = *strongly agree*).

Predictors (Time 1). Predictors were assessed using the Facilitating Conditions Questionnaire (FCQ; McInerney et al., 2005; Yeung, McInerney, & Ali, 2014). This instrument measures seven dimensions: (a) School valuing (4 items, α = .764; e.g., "Doing well at school is really important to my future"), affect toward school (3 items, α = .656; e.g., "The subjects at school interest me"), positive influence by peers (4 items, α = .617; e.g., "Most of my friends want to do well at school"), negative influence by peers (3 items, α = .866; e.g., "My friends say I should leave school as soon as possible"), support from parents (4 items, α = .786; e.g., "If I decided to go on to college or university, my father would encourage me"), negative influence by parents (4 items, α = .902; e.g., "My mother encourages me to leave school as soon as possible"), and support from teachers (3 items, α = .650; e.g., "I get encouragement from some of my teachers to do well at school"). Participants rated each item on a four-point Likert scale (1 = *strongly disagree*, 4 = *strongly agree*).

Data Analysis

Latent Profile Analyses. Analyses were conducted from factor scores representing participants' levels on the eight ISM achievement goals, using Mplus 7.3 (Muthén, & Muthén, 2014) robust Maximum Likelihood estimator (MLR) and taking into account students' nesting within schools with the Mplus design-based correction of standard errors (Asparouhov, 2005). These factors scores are

estimated in standardized units (M = 0, SD = 1) and were saved from measurement models which fully supported the factor validity and measurement invariance of the ISM across genders (see Morin, Boudrias, Marsh, Madore & Desrumaux, 2016; Morin, Meyer et al., 2016, for a discussion of the advantages of using factor scores in LPA). Factor scores can be readily interpreted as deviations from the grand mean expressed in *SD* units and are comparable across genders and profiles. The measurement models used to extract the factor scores are reported in the online supplements.

Previous research led us to expect up to six profiles. However, given the greater number of goals considered in this study, solutions including up to seven latent profiles were considered. In these models, indicators' means, but not their variances, were freely estimated across profiles. Alternative models relying on the free estimation of indicators' variances across profiles converged on improper solutions or did not converge at all, which suggests overparameterization and the need to rely on more parsimonious models (Bauer & Curran, 2003; Chen, Bollen, Paxton, Curran, & Kirby, 2001). Models were estimated based on 5,000 random sets of start values, 100 iterations per random start, and the 200 best solutions retained for final stage optimization. These values were respectively increased to 10,000, 1000, and 500 in the models used to test the similarity of the profiles across genders. Each solution converged on a well-replicated loglikelihood value.

The conditional independence assumption of classical LPA is that the presence of the latent categorical variable representing the profiles will be sufficient to explain all of the observed correlations between the indicators (goals) (Vermunt & Magidson, 2002). This relatively strong assumption is frequently too stringent for real-life settings, and can result in the overextraction of spurious latent profiles (Bauer & Curran, 2003; Peugh & Fan, 2013). Notably, Morin and Marsh (2015) highlighted the unrealism of this requirement when profile indicators can be assumed to reflect a single overarching factor (i.e., global motivation in the present study, e.g., McInerney & Ali, 2006), and proposed factor mixture analyses as a way to relax this conditional independence assumption. In line with this recommendation, the present study rely on a factor mixture approach to LPA (Lubke & Muthén, 2005), relying on the inclusion of a continuous latent factor to control for the variance shared across all indicators. This approach results in the estimation of profiles presenting clearer structural differences on individual achievement goals beyond students' level of global motivation (Morin & Marsh, 2015). In the current study, preliminary analyses further supported the superiority of this approach over that of classical LPA models who tended to result in a reduced level of fit to the data as shown by the comparison of Tables S4 and S5 of the online supplements.

Deciding on the optimal number of profiles to retain can be challenging in LPA applications, and typically relies on (e.g., Marsh et al., 2009; Muthén, 2003): (i) the theoretical meaning and conformity of the solution; (ii) the statistical adequacy of the solution (Bauer & Curran, 2004); (iii) a variety of statistical indicators. These statistical indicators include the Akaike Information Criterion (AIC), the Bayesian information criterion (BIC), the Consistent AIC (CAIC), the sample-adjusted BIC (SABIC), the Lo, Mendell, and Rubin (2001) likelihood ratio test (LMR) and the Bootstrap Likelihood Ratio Test (BLRT). Unfortunately, the BLRT is not available in this study as the models are estimated using a design-based correction of standard errors (accounting for students' nesting within schools). Lower values on the AIC, CAIC, BIC, and SABIC indicate better fitting models, while a non-significant p-value associated with the LMR supports the selection of a model including one less profile. Results from a variety of simulation studies support the efficacy of the CAIC, BIC, and SABIC (e.g., Nylund, Asparouhov, & Muthén, 2007; Tofighi & Enders, 2008). However, with large samples these indicators frequently keep on improving with the addition of latent profiles to the model without ever reaching a minimum (Marsh et al., 2009). When this happens, the information criteria (AIC, CAIC, BIC, and SABIC) need to be inspected to locate the point at which their decrease with the addition of latent profiles become negligible (Morin, Maïano, et al., 2011; Petras & Masyn, 2010). This process can be facilitated by the reliance on a graphical depiction of these indicators (i.e., an elbow plot). Another useful indicator, which should not be used to select the optimal number of profiles, is the entropy (Lubke & Muthén, 2007). The entropy is typically used once the optimal number of profiles has been retained to describe the classification accuracy of the solution. It varies from 0 to 1 and, with higher values suggesting a more accurate classification.

Gender Comparison Models, Predictors, and Outcomes. Once the optimal number of profiles

has been identified separately in each gender group, the degree of similarity of the extracted LPA solution across genders can be examined more systematically using multiple group LPA models. In these models, the grouping variable is specified in Mplus using the KNOWNCLASS function. A systematic framework for multiple group analyses of profile similarity has recently been proposed by Morin (2016; Morin, Meyer et al., 2016). We follow this sequence in the present study. Tests of *configural similarity* first verify whether the same number of profiles can be identified for males and females participants. Then, tests of *structural similarity* verify whether the within-profile means on the achievement goals are similar across genders. In a third step, tests of *dispersion similarity* assess whether the within-profile variances the achievement goals are similar across genders. Fourth, test of *distributional similarity* verify whether the relative size of the profiles is equal across genders.

Distal outcomes (i.e., future aspirations, task perseverance, and learning processes) can then be incorporated to the final latent profile solution based on the results from the first four steps of the sequence. This inclusion permits tests of *explanatory* similarity, in which the equivalence of the within-profile means of these outcomes across genders can be verified. In LPA models including distal outcomes, mean-level differences across specific pairs of profiles or gender groups can be tested using Mplus' MODEL CONSTRAINT function (e.g., Raykov & Marcoulides, 2004; for an application, see Kam, Morin, Meyer, & Topolnytsky, 2016). Finally, predictors (i.e., facilitating conditions) of profile membership can also be integrated to the final latent profile solution based on the results from the first four steps of the sequence through a multinomial logistic regression. The incorporation of predictors allows for tests of *predictive similarity*, by constraining multinomial logistic regressions coefficients to equality across genders. A strong assumption of LPA is that the profiles remain unaffected by inclusion of the predictors and outcomes (Marsh et al., 2009; Morin, Morizot, et al., 2011). To ensure that this did not happen, we followed Morin, Meyer et al. (2016) recommendations and estimated all models including outcomes and predictors using the start values from the model retained in the first four steps.

Across the full sequence, models including equality constraints across gender groups are compared to less restricted models, using the information criteria (AIC, CAIC, BIC, SABIC; Lubke & Neale, 2006; Petras & Masyn, 2010). Lower values on at least two of those criteria suggest that the equality constraints are supported by the data (Morin, Meyer et al., 2016). Annotated Mplus input codes for the gender comparison models estimated here are reported in the online supplements, as well as the correlations among all of variables considered in the present study (see Table S3). Figure 1 presents a graphical representation of the models estimated in the current study, and presents a summary of the various steps used in these profile similarity tests.

Results

Achievement Goal Profiles

The fit indices for solutions including 1 to 7 latent profiles estimated separately in each gender groups are reported in the online supplements (see Table S4). For both genders, the AIC, CAIC, BIC, and SABIC kept on improving with the addition of latent profiles, providing only limited information to help in the selection of the optimal number of latent profiles. The aLMR was not really more informative, suggesting one profile for males and no clear-cut solution for females. To complement this information, we relied on a graphical representation of the values of these information criteria (Morin, Maïano, et al., 2011; Petras & Masyn, 2010). These elbow plots are reported in the online supplements (see Figure S1 and S2), and show that decreases in values of most information criteria tend to flatten around five profiles for both males and females. Examination of the 5-profile solution, and of bordering 4- and 6-profile solutions, showed that all solutions were fully proper statistically. This examination also revealed that adding a fifth profile resulted in the addition of a well-defined qualitatively distinct and theoretically meaningful profile, whereas adding a sixth profile often resulted in the arbitrary division of an existing profile into two distinct profiles differing only quantitatively from one another. The 5-profile solution was thus retained for each gender, providing a reasonable level of classification accuracy with an entropy of .749 for males and .703 for females.

Gender Similarity (Structural, Dispersion, and Distributional) of the Profiles

The goodness-of fit results of the models assessing the similarity of the retained 5-profile solution across genders are reported in Table 1. From an initial unconstrained multiple-group 5-profile model of configural similarity, we first estimated a model of structural similarity by constraining the within-profile means on the achievement goals to be equal across genders. This model resulted in higher values on the AIC, CAIC, BIC, and SABIC, suggesting that the structure of the profiles may not be fully invariant across genders. From this model, we estimated a first model of partial structural similarity, allowing one of the profiles to differ across groups. This model also resulted in higher values on the AIC, CAIC, BIC, and SABIC when compared to the model of configural similarity. We thus estimated a second model of partial structural similarity, in which two of the profiles were allowed to differ across genders. This specific model resulted in lower values on the CAIC and the BIC relative to the model of configural similarity, and was thus retained for the following steps.

Second, we estimated a model of dispersion similarity by constraining the levels of within-profile variability on the achievement goals to be equal across genders for the three structurally invariant profiles. This model resulted in lower values on the AIC, CAIC, BIC and the SABIC than the model of partial structural similarity, thereby supporting the partial dispersion similarity of the profiles. In essence, these results show that, whenever profile structure is equivalent across genders, the level of within-group variability (or homogeneity of the profiles) is also equivalent. Finally, we estimated a model of distributional similarity by constraining the relative sizes (i.e., class probabilities) of all latent profiles to be equal across genders. This model resulted in an increase in the value of all information criteria, showing that the relative sizes of the profiles differed between males and females. As the distribution similarity was not supported, the model for dispersion similarity was retained for interpretation and for the next stages.

The profiles are illustrated in Figure 2, while the exact within-profile means of the achievement goals are reported in the online supplements (Table S6). The relative sizes of the profile are reported in Table 2. Profiles 1 to 3 are equivalent across genders, while the structure of profiles 4 and 5 differs across genders. Profile 1 is characterized by high (task involvement) and moderately high (effort) levels of mastery goals coupled with high levels of competition goals and moderately high levels of praise goals. Levels of social goals (social concern and affiliation) are particularly low, while levels of social power and token reward goals are closer to the average. This "*Mastery-Competition Oriented*" profile describes students who are particularly involved in mastering their schoolwork, more competitive and less likely to care about their classmates in comparison to other students. This profile is slightly more frequent among females (12%) relative to males (8%).

Profile 2 is characterized by average or slightly above average levels on most achievement goals. This "*Moderately Motivated*" profile is similarly frequent among males (36%) and females (37%) students, and is the most prevalent profile for females. In contrast, Profile 3 is characterized by high levels of mastery (task and effort) and social (affiliation and social concern) goals, coupled with low levels of performance (competition and social power) and token reward goals but average levels of praise goals. This "*Mastery-Socially Oriented*" profile characterizes students who especially care about mastering the school content and about their relationships with their classmates in comparison with other students, and is twice as much prevalent among females (23%) relative to males (11%).

Although the results showed that the nature of Profiles 4 and 5 differ across genders, they also suggest that the differences are minimal for Profile 4. Thus, for both males and females, this profile is characterized by high levels of social power and token rewards goals, low levels of task involvement goals and moderately low levels of effort, affiliation, social concern and praise goals. The magnitude of the within-profile discrepancy in levels between mastery goals (low) and social power and rewards goals (high) appears more pronounced among females relative to males, whereas levels of competition goals are slightly higher among males (above average) relative to females (average). Based on similarities across groups, we use the label "*Social Power and Rewards Oriented*" to describe this profile. It is noteworthy that this *Social Power and Rewards Oriented* profile is the one with the highest proportion of males (41%), which are four times more represented in this profile than females (11%). This profile describes students for whom academic motivation appears to be more anchored into a desire to acquire social power and tangible rewards, in comparison with other students, a goal that seems to involve a higher level of competitiveness among males.

In contrast to Profile 4, gender differences in the structure of Profile 5 are clearer. For males, this profile is characterized by high level of mastery (task and effort) goals, a moderately high level of competition goals, average or moderately low levels of social power, affiliation, and social concerns goals, and extremely low levels of extrinsic goals (praise and token). This male-specific "*Mastery Oriented*" only characterizes 4% of the males included in this sample. For females, this profile rather characterizes 17% of "*Moderately Unmotivated*" participants.

Explanatory Similarity of the Profiles.

Distal outcomes (i.e., future aspirations, task perseverance, and learning processes) were added to the final model of partial dispersion similarity. We first estimated a model in which the within-profile levels of outcomes were freely estimated across genders, and contrasted this model with one in which these levels were constrained to be invariant across genders (explanatory similarity). As shown in Table 1, this model resulted in higher values for the AIC, CAIC, BIC, and SABIC, thus failing to support the explanatory similarity of the model. The mean levels of each outcome across genders and profiles, and tests of significance, are reported in Table 3.

These results are fairly consistent across outcomes for males. Thus, levels of future aspirations related to Fame, Wealth, Family and Society, as well as task perseverance and deep learning, tend to be lower in Profile 1 (*Mastery-Competition Oriented*), followed, in order, by Profiles 2 (*Moderately Motivated*), 3 (*Mastery-Socially Oriented*), 4 (*Social Power and Rewards Oriented*), with the highest levels observed in Profile 5 (*Mastery Oriented*). For all of these comparisons, the only few non-significant differences are related to the levels of Fame which are equivalent in Profiles 2 and 3, and to the levels of Family, Society, task perseverance and deep learning which are indistinguishable in Profiles 3 and 4. Levels of future aspirations related to the Career reveal a similar pattern of differences, with the exception that Career aspirations are higher (and similar) in Profiles 3 (*Mastery-Socially Oriented*) and 5 (*Mastery Oriented*) than in Profile 4 (*Social Power and Rewards Oriented*). The only outcome for which the results are different is the reliance on surface learning strategies, with lower levels in Profile 1 (*Mastery-Competition Oriented*) in comparison to any other profile. They are also lower in Profile 3 (*Mastery-Socially Oriented*) than 2 (*Moderately Motivated*) and 4 (*Social Power and Rewards Oriented*), and in Profile 2 than in Profile 4.

Differences between profiles in outcome levels are less consistent for females. The most consistent result is that Profile 2 (*Moderately Motivated*) was associated with lowest scores on every outcome, with the exception of surface learning strategies which are slightly less utilized in Profile 3 (*Mastery-Socially Oriented*). Looking more attentively at differences between the remaining profiles, the results are specific to each outcome. In regard to levels of future aspirations, Fame is lower in Profiles 3 (*Mastery-Socially Oriented*) and 5 (*Moderately Unmotivated*) relative to Profiles 1 (*Mastery-Competition Oriented*) and 4 (*Social Power and Rewards Oriented*). Levels of Career aspirations are lower in Profile 4 (*Social Power and Rewards Oriented*) than in Profiles 1 (*Mastery-Competition Oriented*), 3 (*Mastery-Socially Oriented*), and 5 (*Moderately Unmotivated*). Levels of Wealth aspirations are lower in Profile 3 (*Mastery-Socially Oriented*) than in Profile 5 (*Moderately Unmotivated*), and lower in Profile 5 than in Profiles 1 (*Mastery-Competition Oriented*) and 4 (*Social Power and Rewards Oriented*). Levels of Family aspirations are lower in Profile 5 (*Moderately Unmotivated*) than in Profiles 1 (*Mastery-competition Oriented*), 3 (*Mastery-Socially Oriented*), and 4 (*Social Power and Rewards Oriented*), and higher in Profile 1 than in Profile 3. Levels of Society aspirations are lower in Profile 5 (*Moderately Unmotivated*) relative to Profiles 1 (*Mastery-Competition Oriented*), 3 (*Mastery-Socially Oriented*), and 4 (*Social Power and Rewards Oriented*). Levels of task perseverance are lower in Profile 1 (*Mastery-Competition Oriented*) than in Profile 3 (*Mastery-Socially Oriented*), and in Profile 3 than in Profile 5 (*Moderately Unmotivated*). Levels of deep learning strategies are lower in Profiles 1 (*Mastery-Competition Oriented*) and 5 (*Moderately Unmotivated*) than in Profiles 3 (*Mastery-Socially Oriented*) and 4 (*Social Power and Rewards Oriented*). Finally, levels of surface learning are higher in Profile 4 (*Social Power and Rewards Oriented*) relative to any other profiles, and higher in Profile 2 (*Moderately Motivated*) relative to Profile 3 (*Mastery-Socially Oriented*).

Overall, these findings suggest gender-differentiated relations between profiles and outcomes. This

differentiation could be partly due to the fact that the structure of Profile 5 differs across genders. For males, this profile (*Mastery Oriented*) appears to be associated with some of the most positive outcomes, whereas it (*Moderately Unmotivated*) appears far less desirable for females. However, one very similar result is that Profile 2 (*Moderately Motivated*) tends to be related to low levels on most desirable outcomes for both genders, although the situation is even worse for males corresponding to Profile 1 (*Mastery-Competition Oriented*) suggesting that combining competitive goals with mastery goals has undesired effects for males. Interestingly, this same profile appears to predict relatively strong future aspirations across domains for females, although it remains associated with relatively low levels of task perseverance and deep learning strategies. Another interesting result is that, with few exceptions, Profile 4 (*Social Power and Rewards Oriented*) appears to be associated with relatively positive outcomes among both males and females, in a manner highly similar to that observed in Profile 3 (*Mastery-Socially Oriented*).

Predictive Similarity of the Profiles

Predictors (i.e., facilitating conditions) were finally added to the model of partial dispersion similarity described earlier. We first estimated a model in which the effects of the predictors on the probability of membership into the profiles were freely estimated across genders, and contrasted this model with one in which these relations were constrained to be equal across genders (i.e., predictive similarity). As shown in Table 1, the model of deterministic similarity resulted in lower values for the CAIC, BIC, and SABIC, thus supporting the complete predictive similarity of the model across genders. This result also supports the previous observation that the fourth profile presented similarities across genders by showing that this profile apparently relates similarly to predictors across genders. Interestingly, this result also suggests that the mechanisms involved in the development of the fifth profile (*Mastery-Oriented* for males or *Moderately Unmotivated* for females) share at least some levels of similarity. Nevertheless, it is important to keep in mind that this profile presents a gender-differentiated structure, an issue to which we come back in the discussion. The results from this multinomial logistic regression are reported in Table 4.

Starting with school valuing, the results show that students who tend to value school to a greater extent are more likely to be members of Profile 1 (*Mastery-Competition Oriented*) in comparison to all other profiles, followed by Profile 2 (*Moderately Motivated*) compared to Profiles 3 (*Mastery-Socially Oriented*), 4 (*Social Power and Rewards Oriented*), and 5 (*Mastery Oriented/Moderately Unmotivated*). These students are also more likely to correspond to Profiles 3 (*Mastery-Socially Oriented*) or 5 (*Mastery Oriented/Moderately Unmotivated*) relative to Profile 4 (*Social Power and Rewards Oriented*). Regarding school affect, the results show that students presenting a more positive affect toward school present a higher likelihood of membership into Profile 3 (*Mastery-Socially Oriented*) in comparison to any other profiles, as well as a higher likelihood of membership into Profiles 2 (*Moderately Motivated*) and 5 (*Mastery Oriented/ Moderately Unmotivated*) relative to Profiles 1 (*Mastery-Competition Oriented*) and 4 (*Social Power and Rewards Oriented*). Similarly, these students are more likely to correspond to Profile 1 (*Mastery-Competition Oriented*) relative to Profile 4 (*Social Power and Rewards Oriented*). These results suggest that valuing schooling (i.e., finding that school is useful for more extrinsic reasons) tends to predict membership into profiles characterized by higher levels of academic motivation, but not into profiles in which the key driver of motivation is a mastery-orientation disconnected from performance goals (i.e., Profiles 3 and 5 among males) for which a more intrinsic interest in school (i.e., school affect) appears to be more critical.

Regarding peers, the results show that exposure to positive peer influence predict an increased likelihood of membership into Profile 3 (*Mastery-Socially Oriented*) relative to all other profiles, as well as in Profiles 2 (*Moderately Motivated*), 4 (*Social Power and Rewards Oriented*), and 5 (*Mastery Oriented/Moderately Unmotivated*) relative to Profile 1 (*Mastery-Competition Oriented*). In contrast, higher levels of negative peer influence predict an increased likelihood of membership into Profile 4 (*Social Power and Rewards Oriented*) relative to all other profiles, as well as in Profiles 2 (*Moderately Motivated*) and 5 (*Mastery Oriented/Moderately Unmotivated*) relative to Profiles 1 (*Mastery-Competition Oriented*) and 3 (*Mastery-Socially Oriented*). These results show that positive peer influence predicts a higher likelihood in the profile characterized by the highest levels of social goals (Profile 3) as well as a lower likelihood of membership in the profile characterized by the

lowest levels of social goals (Profile 1). In contrast, negative peer influence rather predicts a greater likelihood of membership into the profile in which the key focus of motivation is the attainment of tangible rewards and social power (Profile 4).

The effects of parental influence on academic motivation profiles appear to be less pronounced than the effects of peers and teachers. More precisely, parental support mainly predicts a an increased likelihood of membership into Profile 1 (*Mastery-Competition Oriented*) in comparison to Profiles 4 (*Social Power and Rewards Oriented*) and 5 (*Mastery Oriented/Moderately Unmotivated*), as well as into Profile 2 (*Moderately Motivated*) in comparison to Profile 5 (*Mastery Oriented/Moderately Unmotivated*). In contrast, negative parental influence predicts a greater likelihood of membership into Profile 4 (*Social Power and Rewards Oriented*) relative to Profiles 1 (*Mastery-Competition Oriented*), 2 (*Moderately Motivated*), and 3 (*Mastery-Socially Oriented*). These results suggest that parental influence appears limited to the prediction of slightly higher levels of global motivation in a pattern that is generally similar, albeit less marked, than the one observed for school valuing.

Finally, higher levels of perceived teacher support predict a higher likelihood of membership into Profile 4 (*Social Power and Rewards Oriented*) relative to all other profiles, as well as in Profile 2 (*Moderately Motivated*) relative to Profiles 1 (*Mastery-Competition Oriented*) and 3 (*Mastery-Socially Oriented)*. Teacher support also predicts a higher likelihood of membership into Profile 5 (*Mastery Oriented/Moderately Unmotivated*) relative to Profile 3 (*Mastery-Socially Oriented).* These results suggest that teacher support, at least within this Asian sample, may encourage the development of motivational profiles characterized by a higher level of focus on external rewards and social power.

Discussion

Adopting a multiple goal perspective, we investigated the extent to which Hong Kong adolescents' achievement goal profiles, their predictors, and their outcomes generalized across genders through a new multiple-group LPA framework. Our results provided strong support to the similarity of most profiles across genders, although key differences were observed. We identified five qualitatively and quantitatively distinct profiles in each gender group, and found that three of these profiles were structurally identical between males and females, that a fourth profile was highly similar across genders, while a fifth profile presented a different structure for males and females. Gender similarity was also strengthened by the fact that all five profiles presented equivalent relations with predictors across males and females. Nevertheless, significant gender differences were observed in the relative prevalence of the various profiles and the associations between the achievement goal profiles and the outcomes. We first discuss the nature of the profiles, before addressing their associations with outcomes and predictors, as well as the implications and limitations of our results.

Gender Differentiation and Similarity in Achievement Goal Profiles

The set of profiles observed here were mostly similar across genders, providing some support to gender similarity in achievement goal profiles. Three of these profiles presented the same structure and level of within-profile variability across genders: (a) *Mastery-Competition Oriented* students seeking to develop their competencies through task mastery, but adopting a competitive and solitary approach to achieve these goals; (b) *Moderately Motivated* students presenting slightly above average levels on most achievement goals; (c) *Mastery-Socially Oriented* students seeking task mastery but this time through the adoption of a collaborative approach. The *Social Power and Rewards Oriented* profile, characterizing students for whom educational achievement mainly appears to represent a way to achieve social power and external rewards, was also generally similar across genders. However males corresponding to this profile presented a lower level of discrepancy between competitive goals (higher levels) and social power (lower levels) than their female counterparts. The fifth profile appeared clearly differentiated across genders, describing *Mastery Oriented* males (who mainly seem to value involvement and effort as a way to master school-related tasks) compared to *Moderately Unmotivated* females (presenting relatively low levels on most achievement goals). We thus identified six clearly distinctive goal combinations, two of them being gender-specific.

Although no prior person-centered study included all eight dimensions of achievement goals considered here, the profiles identified in this current study share many similarities with those

observed by Korpershoek et al. (2015) and Shim and Finch (2014), who assessed social and extrinsic goals among Western (Dutch and Americans) adolescents. Both of these studies identified profiles characterized by high levels of mastery and social goals coupled with relatively low levels of performance goals, corresponding to the *Mastery-Socially Oriented* profile identified here. This profile was twice as prevalent among females (23%) than males (11%). Although no prior study has investigated gender differences in terms of membership in a similar profile, this result is not surprising, given that studies conducted in different countries suggest that females tend to present higher levels of mastery (e.g., Nie & Liem, 2013) and social (e.g., King & Ganotice, 2014; King et al., 2012; Wentzel et al., 2007) goals than males. Although not assessing social goals, Meece and Holt (1993) also showed that females proportion was higher in the high-mastery/low-performance profile.

The *Social Power and Rewards Oriented* profile is similar with the profile characterized by high levels of performance and extrinsic goals identified by Korpershoek et al. (2015). It is interesting that, by considering eight specific goal facets, we were able to observe that the key drivers of motivation for this profile seems to be centered on social status (relative to competition) and external rewards (relative to praise). Among all profiles identified here, this profile is the one presenting the lowest levels of mastery and social goals. The degree of within-profile differentiation among goal levels (i.e., the dominance of social power and rewards goals relative to mastery and social goals) observed in this profile appears more pronounced for females, relative to males. However, this more extreme version of the profile among females also appears to be slightly less prevalent, corresponding to 11% of the females, compared to 41% of the males for the moderate version of the profile. This is in line with observations from previous studies which generally showed that males were more likely to pursue performance goals (Anderman & Young, 1994; Linnenbrink et al., 1999) or to be more frequently represented in performance-driven profiles (Levy-Tossman et al., 2007).

Korpershoek et al. (2015) and Shim and Finch (2014) identified profiles characterized by low levels on all goals, corresponding to the *Moderately Unmotivated* profile identified here among 17% of the females. The absence of a similar profile among males might be related to the greater representation of males (41%) in the *Social Power and Rewards Oriented* profile, which presents relatively low levels on most goals, save for social power and rewards. This suggests that a low level of motivation may exist for some females (at least as measured by the ISM), whereas less motivated males will continue to be driven by the possibility to be rewarded or obtain social status for their performance. However, in previous studies of North American students (Bouffard et al., 1995; Meece & Holt, 1993), the prevalence of males in profiles characterized by low achievement goals was higher. This could possibly be related to the cultural context in which the present study was conducted, suggesting that male students from Hong Kong may show a stronger desire for social power and rewards, even in the less motivated profiles. Eastern cultures tend to be more hierarchical (leading to a greater need to “succeed”) and embedded (leading to more social pressure to achieve). As such, social power, rewards, and competition could represent key drivers of achievement in these cultures, even for students lacking other forms of motivation (Dekker & Fischer, 2008). Cross-cultural research based on PIT usually found that performance goals tend to be higher in non-Western cultures (e.g., Asian, Lebanese, Papua New Guinean, etc.; Magson et al., 2014; McInerney, 2008; 2012).

Profiles similar to the three profiles discussed above were also identified in previous cluster analytic studies focusing on the classical mastery-performance dichotomy, which have generally identified a mastery-dominated profile, a performance-dominated profile, an unmotivated profile, and a high mastery/high performance profile (e.g., Daniels et al. 2008; Turner, Thorpe, & Meyer, 1998), mainly among samples of North American children and young adults. In addition to the previously discussed *Mastery-Socially Oriented* profile, the *Mastery Oriented* profile (males only) also seems to correspond to the mastery-dominant profiles identified in these studies. Nevertheless, this profile only represents a low percentage of the males (4%) and was not observed among females. It thus seems that when endorsing high levels of mastery goals, scores on social goals tend to be either higher or lower than average, particularly among females. In contrast, Korpershoek et al. (2015) and Shim and Finch (2014) both found that high scores on mastery goals were systematically combined with high scores on social goals. Thus, they did not identify a profile similar to the *Mastery-Competition Oriented* one, in which students seem particularly concerned about getting involved in their academic

tasks and performing better than their classmates, while being less inclined to help them or seek social affiliation. However, this profile corresponds well to the high mastery/high performance profile identified in previous studies in which social and extrinsic goals were not considered (e.g., Daniels et al. 2008; Turner et al., 1998). A possible explanation for this difference of results could be related to the relatively small size of this profile in the current study (11.8% of females; 8.4% of males), which could make it harder to identify in studies relying on smaller samples (e.g., N = 446 in Shim and Finch, 2014). As mentioned above, competition (performance) goals may be more marked for the Hong Kong students composing our sample, which could possibly explain this distinctive profile not identified by Korpershoek et al. (2015) and Shim and Finch (2014).

No profile characterized by high levels on each achievement goals was identified in this study, nor in Shim and Finch's (2014) study, although one such profile was identified by Korpershoek et al. (2015). However, the current study and Shim and Finch (2014) both identified a *Moderately Motivated* profile presenting slightly above average levels on all achievement goals. Thus, this discrepancy seems to mainly reflect the overall level of motivation that characterizes this profile rather than its specific nature. This profile did not differ across genders, and was equally prevalent across males (36%) and females (37%), in line with previous results (Levy-Tossman et al., 2007).

Although our research was conducted among Hong Kong adolescents, the identified profiles were generally similar to those obtained in studies conducted with European and American adolescents (Korpershoek et al., 2015; Shim & Finch, 2014). This similarity supports the generalizability of multiple goal configurations across various cultures. Nevertheless, Hong Kong remains a unique Asian culture which, as a former English colony, is likely to lie somewhere in the middle of the Western-Eastern cultural continuum. Further research will be needed to more systematically test the extent to which our results really generalize to a greater variety of cultural contexts.

Outcomes of Achievement Goal Profiles

In order to more precisely assess the relative desirability of each achievement goal profile, we looked at associations between the profiles and a variety of important educational outcomes, including students' learning processes, and task persistence, and future aspirations. These outcomes were selected given their critical importance in shaping students educational and career choices occurring later in life (e.g., Beal & Crockett, 2010). The observed associations differed across genders, suggesting gender-differentiated processes in the consequences of achievement goal profiles. This result was partly expected, given that two profiles out of five differed across genders and that previous studies found both differences and similarities in the associations between achievement goals and outcomes (Gherasim et al., 2012; Linnenbrink et al., 1999; Ryan & Shim, 2008).

The *Moderately Motivated* profile appeared to be one of the least desirable profiles identified here, suggesting that it does substantively differ from the high mastery/high performance profile identified in previous studies (Daniels et al. 2008; Korpershoek et al., 2015; Turner et al., 1998). Indeed, this profile was associated with the lowest scores on most desirable outcomes among females, and to the second to lowest scores for males. These results suggest that for both genders, showing a slightly above average level on all types of achievement goals is generally less adaptive than showing moderately high to high levels on some achievement goals. For females, this profile was even associated with worse outcomes than the *Moderately Unmotivated* one in regard to future aspirations and deep learning strategies. A possible interpretation for this difference is that, among females with low levels of achievement motivation, future aspirations might possibly be anchored in other types of non-academic skills. This result is supported by our analyses of predictors, showing that *Moderately Unmotivated* students tend to put less instrumental value in schooling and feel less encouraged by their parents to pursue postsecondary education than the *Moderately Motivated* students. In contrast, among moderately motivated students, future aspirations may remain associated with a harder to attain form of academic success anchored in too many objectives. This simultaneous pursuit of multiple objectives may reflect either a difficulty in establishing clear priorities, or perhaps even the presence of conflicting priorities, suggesting that we could probably relabel this profile "*Ambivalent*" to reflect this indecision. Without clear success criteria (i.e., mastery, or competition, or rewards), future aspirations may remain more confusing to define for both male and female students. This

Ambivalent profile could also be particularly detrimental in early adolescence, when individuals' sense of identity remains fragile and changing in response to the multiple biopsychosocial transformations that mark the beginning of this critical developmental period.

For males, the *Mastery-Competition Oriented* profile seemed even less adaptive, and associated with the lowest scores on all future aspirations, as well as on task perseverance and deep learning strategies. A plausible explanation could be that higher levels of competitive performance goals tend to be associated with higher levels of anxiety (Linnenbrink, 2005), which in turn could generate worries and negative future expectations (MacLeod & Byrne, 1996). This observation is consistent with our prior interpretation that seeking to accomplish too many conflicting objectives simultaneously, or being unable to prioritize, may yield deleterious effects. Still, this observation suggests that what represents the most suboptimal combination differs across genders. Indeed, for females, this *Mastery-Competition Oriented* profile was associated with higher future aspirations in comparison to most other profiles and generally positive outcomes. Thus, females with higher competitive tendencies but a lower desire to help their peers and collaborate with them seemed more likely to nourish higher ambitions about their future. Gender differences in terms of competitiveness, with females being generally less competitive than males, have often been invoked to explain gender inequality in access to high status positions (Niederle & Vesterlund, 2011). Taken together, these results suggest that, perhaps due to males' higher competitive tendencies (Anderman & Young, 1994; Harackiewicz et al., 1997; Linnenbrink et al., 1999; McInerney et al., 1998), strong competitive objectives may interfere with the pursuit of mastery goals. Although this profile was only observed in a small minority of males (4%), the predominantly *Mastery Oriented* profile was associated with the most desirable outcomes among males. In contrast, more interference may be created by combining multiple goals among females, perhaps due to their higher affiliation tendencies (King et al., 2012; Patrick et al., 1997; Ryan et al.. 1997; Wentzel, 1993; Wentzel et al., 2007), which may interfere with the pursuit of incompatible goals (e.g., competition, rewards). This hypothesis is also coherent with the general interdependence (females) and independence (males) tendencies that seem to be intertwined with gender-differentiated socialization (Cross & Madson, 1997). Still, the multiple goals combination of the *Moderately Motivated* profiles also appeared to be associated with undesirable results for male students, for whom this profile came second to last in terms of outcomes.

In line with prior research showing the benefits of adopting mastery or social goals alone (Hulleman et al., 2010; King et al., 2010, 2013; Watkins, McInerney, & Lee, 2002) or in combination (Korpershoek et al., 2015; Shim & Finch, 2014; Wentzel, 1993), the *Mastery-Socially Oriented* profile was associated with desirable outcomes for males and females. Perhaps more interesting is the observation that the *Social Power and Praise Oriented* profile presented similar outcomes levels as the *Mastery-Socially Oriented* profile. Looking at the nature of the outcomes, it is not surprising that seeking more social power and extrinsic achievement goals like rewards predicts higher future aspirations in more "extrinsic" areas (e.g., fame and wealth; Lee et al., 2010), as well as surface learning strategies (Elliot et al., 1999). More surprising is the similar association of these two profiles with family and society aspirations (considered to be more intrinsic in nature), with task perseverance, and with the adoption of deep learning strategies. Still, it is important to recall that, although Lee et al. (2010) reported stronger associations between mastery goals (relative to performance goals) and intrinsic future aspirations (career, family, society), and between performance goals (relative to mastery goals) and extrinsic aspirations (fame and wealth), their results also showed positive associations between performance goals and intrinsic aspirations. Additionally, in our study, family and society aspirations were assessed in a manner that is consistent with social power and extrinsic rewards (e.g., to support or to provide for the family, to contribute to or to develop society). Although it is more rarely the case than for mastery goals, studies also found positive associations between performance goals and deep learning strategies (Midgley et al., 2001), as well as task persistence (Elliot et al., 1999). These positive relations could be more likely to occur when social power goals are combined with reward goals. Further research is clearly needed to explore this possibility.

Predictors of Achievement Goal Profiles

Various facilitating conditions were significantly associated with membership in the achievement goal profiles, and these associations did not differ across genders. This result is consistent with the

only two studies reviewed earlier which investigated (and did not find) gender differences in the associations between predictors and achievement goals (Chen & Pajares, 2010; Nie & Liem, 2013). Although specific associations differed across predictors, a general pattern emerged for the *Social Power and Rewards Oriented* profile (Profile 4). The likelihood of membership in this profile was mostly associated with lower scores on the positive facilitating conditions (school valuing, positive affect toward school, positive peer influence, parental support) and higher scores on the negative facilitating conditions (negative influence from peers and parents). Thus, students with more negative academic attitudes and receiving less than positive forms of academic support from peers and parents also tend to show higher desire to gain social recognition and rewards. This result is in part consistent with Urdan's (1997) results showing that affiliation with peers who did not value education was negatively associated with the adoption of mastery goals but positively associated with the adoption of extrinsic goals. What is intriguing is the observation that this profile was associated with relatively positive outcomes. Students who received more encouragement from teachers were also more likely to be members of this profile, suggesting that teacher support may help those coming from a background that does not value education to adopt alternative forms of academic goals, which might help them to achieve positive academic outcomes. It is in fact plausible that teachers may give more attention to students who appear to be less motivated by their schoolwork or are experiencing more difficulties. In turn, these students might then feel more supported, leading them to refocus their attention on academic coursework. Although this interpretation is fully consistent with a wide range of studies which have shown that teacher support may be particularly beneficent for at-risk students from disadvantaged backgrounds (Hamre & Pianta, 2001; Meehan, Hughes, & Cavell, 2003), research would to do well to consider a wider range of variables describing teachers' support in order to better describe the developmental mechanisms underlying these relations.

In contrast, students who enjoy school intrinsically and interact with peers who value education are more likely to also be motivated to master their schoolwork and to pursue school-related interactions with their classmates (*Mastery-Socially Oriented*). These results are consistent with Harackiewicz et al. (2008) who found reciprocal relations between academic interest and the adoption of mastery goals. Students from this profile are also less likely to pursue goals oriented by performance or by the attainment of external rewards, and thus seem motivated by the fact that they like school for its own sake, for learning and for sharing these learning experiences with their friends. As discussed earlier, this profile was associated with similar outcomes than the *Social Power and Rewards Oriented* one, which makes it complicated to suggest interventions in terms of best practices. However, what our results suggest is that school enjoyment and academic support from parents and peers are associated with a higher likelihood of endorsing a more desirable profile characterized by higher levels of mastery and social goals, which in turns presents clear associations with positive education outcomes. This mechanism appears to describe students who come into the classroom with an already positive motivational profile with access to high levels of social support for schooling. For these students, teacher support is unlikely to make a big difference (Hamre & Pianta, 2001; Meehan et al., 2003). In contrast, for students coming into the classroom with more negative attitudes, and low levels of pre-existing proactive academic support, teacher support appears more likely to be beneficial. As such, although the current results are uninformative regarding the best role for teachers to adopt with already motivated and well-supported students, they suggest that there is value in providing support to the least motivated students. Clearly, future research is needed in this area.

Furthermore, students who value school for more instrumental or extrinsic reasons are more likely to also be characterized by a *Mastery-Competition Oriented* profile. Parental support, which was assessed in this study by items focusing mainly on the valuing of education for instrumental reasons, also tends to be associated with a higher likelihood of membership into this profile. Perceiving that academic success is the key to accessing desired educational or professional opportunities may be accompanied by a desire to master school content, but the rarity of these opportunities (highly paid job, college scholarships, etc.) may lead to the adoption of a competitive approach. In contrast, affiliation with friends who care about school and share high educational aspirations tends to be associated with a lower likelihood of membership into this profile. As this profile was the least desirable in terms of outcomes for males, it appears that schools would do well to carefully assess the extent to which they value and encourage school instrumentality. For males, at least in our study, this

focus on instrumentality seemed to be accompanied by negative outcomes. Importantly, future research should devote more attention to the developmental mechanisms underlying this relation.

Whereas the structure of Profile 5 varies across genders (Mastery Oriented males vs. *Moderately Unmotivated* females), these gender-specific profiles shared similar associations with the predictors. To understand this intriguing result, it is important to reiterate that the associations between predictors and profiles were assessed via multinomial regressions. Multinomial logistic regressions compare the influence of predictors on the probability of membership into each specific profile in comparison with the other profiles. Because of the nature of these comparisons, the presence of similar relations between predictors and the remaining four profiles across genders might partly explain why the relation into the remaining profiles remain identical for purely statistical reasons. However, although different, Profiles 5 also share structural characteristic for males or females that could explain some of these similarities. In comparison to the other profiles, boys and girls corresponding to Profile 5 present average to slightly below average levels on the social power, affiliation, and social concern goals. Furthermore, it is also important to keep in mind that Profile 5 is relatively more frequent among females relative to males (17.2 vs. 4.3 %), which may have reduced the statistical power to locate differences. Further studies should pay attention to this particular result, focusing on an even wider range of predictors to better identify the developmental mechanisms at play in the emergence of these gender-differentiated profiles.

Theoretical Implications

Using eight distinctive types of achievement goals, our results extended and supported the multiple goals perspective in the academic area. To our knowledge, our study is the first to separately examine achievement goal profiles for males and females (five for each gender), while considering the eight distinct types of goal facets proposed by PIT, and to rely on a quantitative comparison process to assess the similarity of the profiles across genders. Our results supported the value of considering not only social and extrinsic goals, but also the goal facets proposed by PIT. Indeed, many of the profiles were meaningfully defined on the basis of a subset of facets associated with each goal.

Four profiles were similar across genders, whereas the structure of the fifth differed across genders. Furthermore, the relative size of the profiles differed across genders for the *Mastery-Socially Oriented* profile (more frequent among females) and the *Social Power and Rewards Oriented* (more frequent among males). These size differences are well-aligned with the well-documented tendency to ascribe greater value to social interactions and social goals for females relative to independence and status for males (Cross & Madson, 1997; Helgeson, 1994). In particular, these differences might have been made more pronounced by the intensification of gender socialization processes that characterizes adolescence (Hill & Lynch, 1983; Ruble et al, 2006). The differences observed here are thus likely to be attenuated among children, before the onset of puberty and the intensification of gendered socialization, or among young adults, whose identity becomes more integrated, thus limiting the impact of gender-related socialization. Research covering longer developmental spans is required to better document how the motivational processes identified generalize to other developmental periods.

Interestingly, facilitating conditions showed similar association with profiles across genders, whereas the outcomes of those profiles varied across genders. For males, the *Mastery Oriented* profile was associated with the most positive outcomes, followed by the *Mastery-Socially Oriented* and the *Social Power and Rewards Oriented* profiles. For females, the *Mastery-Socially Oriented* and the *Social Power and Rewards Oriented* profiles were associated with the most desirable outcomes, although the *Mastery-Competition Oriented* profile was also associated with future aspirations. In contrast, for males, the *Mastery-Competition Oriented* profile was the least desirable. Similarly, for males and females, the moderate adoption of multiple goals (*Moderately Motivated*) was associated with relatively negative outcomes. These last results suggest that there might be gender-differentiated risks to the adoption of multiple goals when some of these goals interfere with the pursuit of others. Future studies should specifically focus on unpacking the gender-differentiated mechanisms underlying these interferences. In sum, our results support a multidimensional goal approach, and even suggest that a combination of social power and extrinsic goals can, for some outcomes, be as beneficial as the combination of mastery and social goals. It is noteworthy that a high level of

competition goals does not seem as detrimental for women, particularly in regard to future aspirations.

Limitations and Further Studies

Some limitations warrant attention when considering the results. First, although our longitudinal design includes two time waves, each variable was only measured once (precluding the assessment of longitudinal change) and both predictors and achievements goals were simultaneously assessed at the first time wave. Despite the fact that both PIT and previous results support the proposed sequence, interpretations should be done with caution. Further longitudinal studies would be needed to support the suggested chronology and to test potential reciprocal and directional relations.

Second, this study only considered a limited set of self-reported predictors and outcomes of the identified profiles. Relying on self-reports might have resulted in some subjective biases in ratings of constructs related to parents, peers, and teacher. Similarly, it might have caused some inflation of the observed relations (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003), although shared method biases are likely to be limited by the reliance on a multivariate analytical framework (for a mathematical demonstration, see Siemsen, Roth, & Olivera, 2010) and on person-centered analyses (Meyer & Morin, 2016). Still, future research would greatly benefit from a consideration of a broader range of covariates and the reliance on more robust multimethod assessment procedures (e.g., parent or teacher rating, institutional data). For instance, various dimensions of teachers' classroom management practices, quality of peer relationships, or parenting style could have enriched our understanding of the development of achievement goal profiles. Similarly, it would be interesting to consider a broader range of educational outcomes, including achievement, attainment, dropout, and career success.

Third, PIT and the ISM only consider the approach (versus avoidance) orientation of these achievement goals. This decision is consistent with research showing clearer relations between approach goals and positive academic outcomes (e.g., Senko et al., 2011), as well as a relatively strong positive correlation between the approach and avoidance facets of achievement goals, particularly for performance goals (Law, Elliot, & Murayama, 2012). Still, we acknowledge that each goal may have an avoidance counterpart (Murayama, Elliot, & Friedman, 2012). Our objective was to consider the broad range of goal facets proposed by the PIT, and to do so while relying on measures already validated among a gender-differentiated samples (i.e., the ISM: Ganotice, Bernardo, & King, 2012; King & Watkins, 2013; McInerney, 2012). The assessment of social goals seemed especially relevant in the investigation of gender differences, as females frequently scored higher than males on social goals (King & Ganotice, 2014; King et al., 2012; Patrick et al., 1997; Wentzel, 1993). However, a natural extension of this study would be to develop an extended version of the ISM including both an approach and an avoidance dimension for each goal facet.

Fourth, our study was conducted among Hong Kong adolescents, suggesting that the results might not fully generalize to students from other cultural groups. Although the structure of the identified profiles was mostly similar to those obtained in Western cultures and thus supported a certain degree of generalizability, variations were also observed and could be related to cultural differences. Moreover, the association between the predictors or the outcomes and our specific profiles, as well as observed patterns of gender differences or similarities, could also differ across cultures. Additionally, the shape of the identified profiles, as well as their relative size and associations with predictors and outcomes, are also likely to fluctuate as a function of students' development stage, educational level, or educational pathway. For instance, the *Moderately Unmotivated* profile is likely to be less represented in samples of university students, and perhaps over-represented in samples of special education students. Thus, further research would do well to focus some attention on potential differences across cultures, development stages, educational level and pathways, as well as on the stability of the identified profiles over time, particularly across the critical life transitions.

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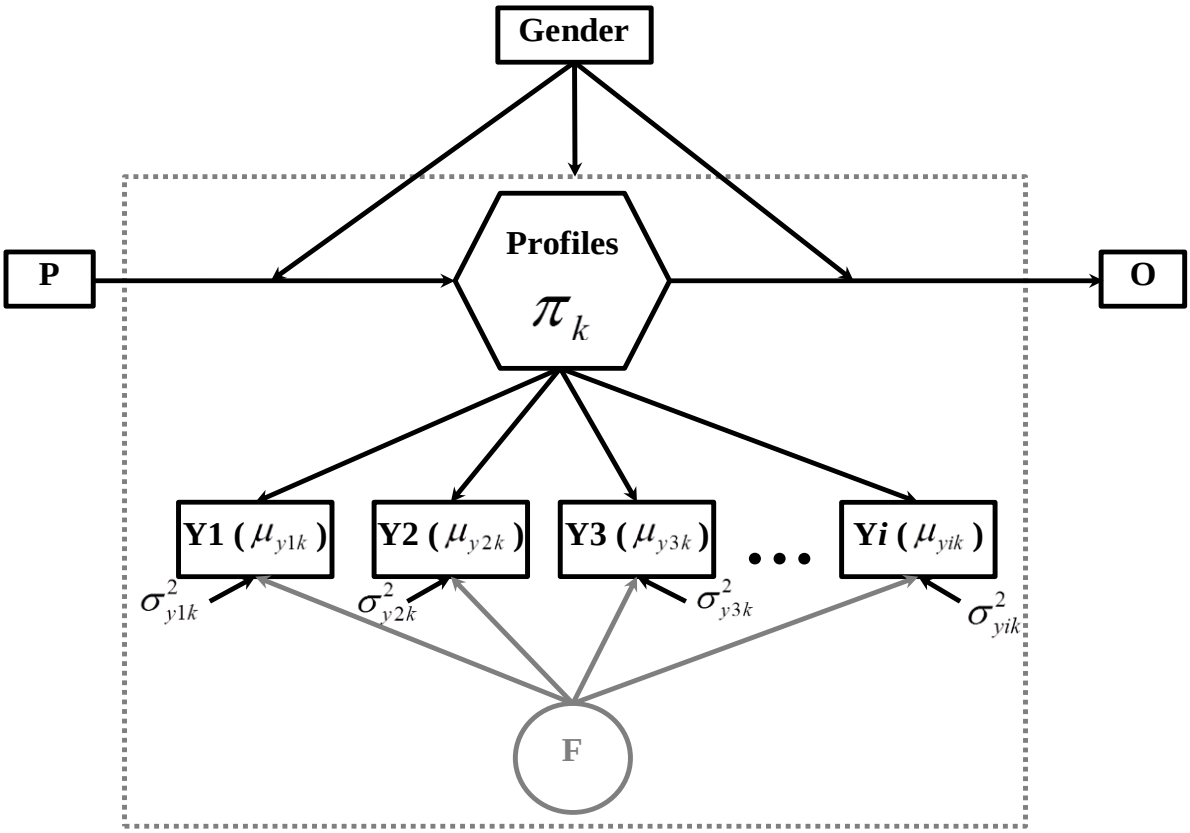

Figure 1. Graphical illustration of the models tested on the present study.

Note. The generic LPA model is expressed as $\sigma_i^2 = \sum_{k=1}^{K} \pi_k (\mu_{ik} - \mu_i)^2 + \sum_{k-1}^{K} \pi_k \sigma_{ik}^2$ (e.g., Lazarsfeld, & Henry, 1968; Peugh & Fan, 2013). For *k* latent profiles estimated from *i* observed indicators (*y1* to *yi*), the LPA model decomposes the variance into between-profile (the first term) and within-profile (the second term) components. In this expression, the profile-specific means (μ_{ik}) and variances (σ_{ik}^2) of the observed indicators are expressed in relation to the density function π_k, reflecting the proportion of participants in each profile. In the current study, a continuous latent factor (F) is added to the model to control for global motivation tendencies shared across indicators (greyscale). This factor mixture model (latent profile model with the continuous latent factor) is enclosed in a greyscale box marked with doted lines and related to gender, to show that the complete model can be freely estimated in both gender groups. Predictors (P) can then be added to this model via a multinomial logistic regression, and outcomes (O) can be added and specified as additional profile indicators. Gender is specified as a moderator of these relations between predictors, profiles and outcomes to show that these relations can be freely estimated across genders. In this figure, the latent categorical variable representing the profiles is illustrated by the hexagon, the latent continuous factor (F) is represent by a circle, and the observed variables (indicators y1 to yi, predictors P, outcomes O and gender) are represented by rectangles. Tests of *configural similarity*, simply involve the estimation of the same number of profiles (k) across groups. Tests of *structural similarity* constrain the within-profile means (μ_{ik}) to equality across groups. Tests of *dispersion similarity* constrain the within-profile variances (σ_{ik}^2) to equality across groups. Tests of *distributional similarity* constrain the relative size of the profiles to equality across groups (π_k). Tests of *predictive similarity* constrain the logistic regressions between predictors (P) and profiles to equality across groups. Finally, tests of *explanatory similarity* constrain the relations between profiles and outcomes (O) to equality across groups.

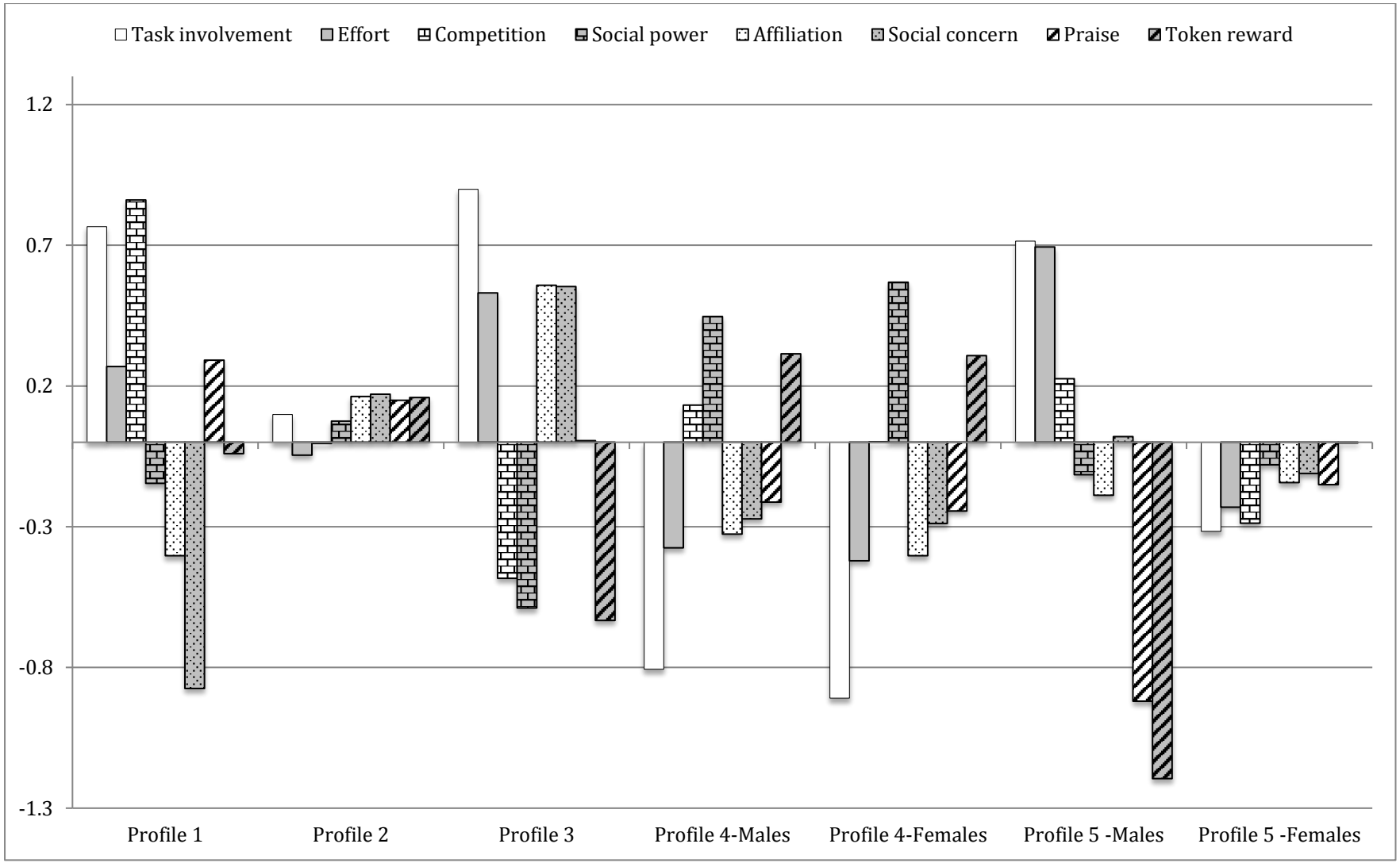

Figure 2. Final Profile Solution. Profile 1 = *Mastery-Competition Oriented*; Profile 2 = *Moderately Motivated*; Profile 3 = *Mastery-Socially Oriented*; Profile 4 = *Social Power and Rewards Oriented*; Profile 5 for Males = *Mastery Oriented*; Profile 5 for Females = *Moderately Unmotivated*.

Table 1
Results from the Latent Profiles Analyses.

Model	LL	#fp	Scaling	AIC	CAIC	BIC	SABIC	Entropy
Final 5-Profile Model								
Male (*n*=4221)	-38689.255	60	2.4078	77498.509	77939.379	77879.379	77688.724	.749
Female (*n*=3627)	-32049.179	60	2.7730	64218.357	64650.127	64590.127	64399.477	.703
Tests of Profile Similarity								
Configural	-76276.286	113	3.4485	152778.572	153678.958	153565.958	153206.867	.809
Structural (M)	-76484.039	73	4.2673	153114.078	153695.743	153622.743	153390.763	.801
Partial Structural (part.M) 4 equivalent profiles	-76436.666	81	4.0720	153035.331	153680.740	153599.740	153342.339	.803
Partial Structural (part.M) 3 equivalent profiles	-76355.346	89	3.7858	152888.692	**153597.845**	**153508.845**	153226.021	.806
Dispersion (part.M, part.V) 3 equivalent profiles	-75952.622	89	3.8354	**152083.245**	**152792.398**	**152703.398**	**152420.574**	.778
Distributional (part.M, part.V, P) 3 equivalent profiles	-76123.139	85	3.8088	152416.278	153093.559	153008.559	152738.446	.800
Explanatory Similarity								
Relations between profiles and outcomes freely estimated	-120780.624	97	3.7932	241755.249	242528.146	242431.146	242122.900	.916
Relations between profiles and outcomes invariant	-122449.825	57	5.1245	245013.650	245467.827	245410.827	245229.692	.931
Predictive Similarity								
Relations between predictors and profiles freely estimated	-46465.060	65	2.0221	93060.120	93547.438	93482.438	93275.891	.799
Relations between predictors and profiles invariant	-46510.806	37	2.7390	93095.613	**93373.009**	**93336.009**	**93218.436**	.798

Note. These analyses are all based on a factor mixture approach to latent profile analyses, including a class-invariant latent factor controlling for global levels of motivation; LL: Model LogLikelihood; #fp: Number of free parameters; Scaling = scaling factor associated with MLR loglikelihood estimates; AIC: Akaïke Information Criteria; CAIC: Constant AIC; BIC: Bayesian Information Criteria; SABIC: Sample-Size adjusted BIC; M: Means; V: Variances; P: Class probabilities; *: $p < .01$.

Table 2
Relative Size of the Profiles (%)

	Profiles				
Gender	1	2	3	4	5
Male (*n* = 4221)	8.41	35.54	10.83	40.96	4.26
Female (*n* = 3627)	11.88	37.39	22.97	10.53	17.23

Note. Profile 1 = *Mastery-Competition Oriented*; Profile 2 = *Moderately Motivated*; Profile 3 = *Mastery-Socially Oriented*; Profile 4 = *Social Power and Rewards Oriented*; Profile 5 for Males = *Mastery Oriented*; Profile 5 for Females = *Moderately Unmotivated*.

Table 3

Associations between Profile Membership and Future Aspirations, Perseverance and Learning Processes.

Motivation	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Significant differences
Males FA Fame	1.821	2.509	2.531	2.974	3.506	1<2=3<4<5
Females FA Fame	2.898	2.402	2.655	3.024	2.572	2<3=5<1=4
Males FA Career	1.739	3.011	3.941	3.922	3.954	1<2<4<3=5
Females FA Career	3.967	3.007	3.944	3.878	3.956	2<4<3<1, 2<4<3=5, 1=5
Males FA Wealth	1.971	2.973	3.518	3.763	3.818	1<2<3<4<5
Females FA Wealth	3.738	2.957	3.522	3.724	3.598	2<3<5<1=4
Males FA Family	2.161	3.145	3.826	3.847	3.932	1<2<3=4<5
Females FA Family	3.762	3.083	3.803	3.748	3.659	2<5<1=4, 2<5<3=4, 1<3
Males FA Society	2.015	2.905	3.246	3.346	3.803	1<2<3=4<5
Females FA Society	3.299	2.872	3.344	3.363	3.137	2<5<1=3=4
Males Perseverance	2.303	2.810	2.927	2.882	3.341	1<2<3=4<5
Females Perseverance	2.808	2.736	2.883	2.811	2.763	2<1<3, 2=4=5, 1=4=5, 3<5, 3=4
Males Deep Learning	2.195	2.843	2.994	2.940	3.428	1<2<3=4<5
Females Deep Learning	2.883	2.783	3.000	3.002	2.866	2<1=5<3=4
Males Surface Learning	2.151	2.587	2.437	2.694	2.725	1<3<2<4, 1<5, 2=5, 3=5, 4=5
Females Surface Learning	2.514	2.542	2.474	2.791	2.557	1=2=5<4, 1=3=5<4, 3<2

Note. FA= Future aspirations; These analyses are all based on a factor mixture approach to latent profile analyses, including a class-invariant latent factor controlling for global levels of motivation. Profile 1 = *Mastery-Competition Oriented*; Profile 2 = *Moderately Motivated*; Profile 3 = *Mastery-Socially Oriented*; Profile 4 = *Social Power and Rewards Oriented*; Profile 5 for Males = *Mastery Oriented*; Profile 5 for Females = *Moderately Unmotivated*.

Table 4

Results from Multinomial Logic Regressions for the Effects of Facilitating Conditions on Profile Membership.

	Latent profile 1 vs. 2		Latent profile 3 vs. 2		Latent profile 4 vs. 2		Latent profile 5 vs. 2		Latent profile 1 vs. 3	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
School Valuing	1.738(0.178)**	5.684	-0.499(0.164)**	0.607	-0.991(0.113)**	0.371	-0.555(0.146)**	0.574	2.236(0.188)**	9.358
Affect Toward School	-0.382(0.086)**	0.682	1.248(0.190)**	3.483	-0.726(0.125)**	0.484	0.019(0.134)	1.019	-1.630(0.192)**	0.196
Positive Peer Influence	-0.536(0.163)**	0.585	0.778(0.213)**	2.177	-0.170(0.122)	0.844	-0.016(0.116)	0.984	-1.314(0.272)**	0.269
Negative Peer Influence	-0.576(0.226)*	0.562	-0.954(0.241)**	0.385	0.962(0.120)**	2.617	0.162(0.166)	1.176	0.378(0.211)	1.459
Parental Support	0.150(0.146)	1.162	-0.034(0.137)	0.967	-0.162(0.130)	0.850	-0.281(0.139)*	0.755	0.184(0.130)	1.202
Parental Neg. Influence	-0.406(0.219)	0.666	-0.138(0.230)	0.871	0.321(0.134)*	1.379	-0.014(0.202)	0.986	-0.268(0.169)	0.765
Teachers Support	-0.370(0.111)**	0.691	-0.557(0.135)**	0.573	0.299(0.117)*	1.348	-0.051(0.201)	0.950	0.187(0.121)	1.206
	Latent profile 4 vs. 3		Latent profile 5 vs. 3		Latent profile 1 vs. 4		Latent profile 5 vs. 4		Latent profile 1 vs. 5	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
School Valuing	-0.492(0.132)**	0.611	-0.056(0.086)	0.945	2.728(0.196)**	15.304	0.436(0.115)**	1.546	2.293(0.198)**	9.900
Affect Toward School	-1.973(0.218)**	0.139	-1.229(0.204)**	0.293	0.343(0.145)*	1.410	0.745(0.145)**	2.106	-0.401(0.172)*	0.669
Positive Peer Influence	-0.948(0.213)**	0.388	-0.794(0.169)**	0.452	-0.366(0.200)*	0.694	0.154(0.149)	1.166	-0.520(0.202)*	0.595
Negative Peer Influence	1.916(0.211)**	6.792	1.115(0.320)**	3.051	-1.538(0.249)**	0.215	-0.800(0.177)**	0.449	-0.738(0.296)*	0.478
Parental Support	-0.128(0.154)	0.880	-0.247(0.170)	0.781	0.312(0.150)*	1.366	-0.118(0.135)	0.888	0.431(0.173)*	1.538
Parental Neg. Influence	0.459(0.223)*	1.583	0.124(0.289)	1.132	-0.727(0.199)**	0.483	-0.336(0.188)	0.715	-0.391(0.297)	0.676
Teachers Support	0.856(0.160)**	2.353	0.506(0.246)*	1.658	-0.668(0.133)**	0.513	-0.350(0.158)*	0.705	-0.318(0.212)	0.727

Note. These analyses are all based on a factor mixture approach to latent profile analyses, including a class-invariant latent factor controlling for global levels of motivation; SE: standard error of the coefficient; OR: Odds Ratio. The coefficients and OR reflects the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile; **: $p < .01$; *: $p < .05$. Profile 1 = *Mastery-Competition Oriented*; Profile 2 = *Moderately Motivated*; Profile 3 = *Mastery-Socially Oriented*; Profile 4 = *Social Power and Rewards Oriented*; Profile 5 for Males = *Mastery Oriented*; Profile 5 for Females = *Moderately Unmotivated*.

Online Supplemental Materials for:

Achievement Goal Profiles Among Adolescent Males and Females

Sections

Preliminary Measurement Models and Tests of Measurement Invariance Across Gender

Preliminary measurement models for achievement goals were estimated using Mplus 7.3 (Muthén & Muthén, 2014). These models were estimated as multiple group models, allowing for the estimation of similar models across gender and the progressive integration of invariance constraints to the models. These models included, in each group, eight correlated factors (task involvement, effort, competition, social power, affiliation, social concern, praise, and token rewards).

The measurement models were estimated using exploratory structural equation modeling (ESEM; Asparouhov & Muthén, 2009; Marsh et al., 2009; Morin, Marsh, & Nagengast, 2013). ESEM offers the possibility to integrate features of CFA, structural equation modeling (SEM), and exploratory factor analysis (EFA) in a single framework. This decision is based on the results from simulation studies (Asparouhov & Muthén, 2009; Sass & Schmitt, 2010; Schmitt & Sass, 2011) and studies of simulated data (Marsh, Lüdtke, Nagengast, Morin, & Von Davier, 2013; Morin, Arens, & Marsh, 2015) showing that forcing cross loadings (even as small as .100, Marsh et al., 2013) present in the population model to be exactly zero according to typical CFA specification forces these cross loadings to be expressed through an inflation of the factor correlations. In contrast, these same studies show that the free estimation of cross-loadings, even when none are present in the population model, still provides unbiased estimates of the factor correlations (also see Asparouhov, Muthén, & Morin, 2015; Morin et al., 2015). Importantly, recent studies also conducted on motivational data have also shown the clear advantages of using ESEM (Guay, Morin, Litalien, Valois, & Vallerand, 2015; Litalien, Guay, & Morin, 2015). Furthermore, it is now possible to rely on a confirmatory approach to the estimation of EFA/ESEM models though the use of target rotation (Asparouhov & Muthén, 2009; Browne, 2001). Target rotation allows for the pre-specification of target loadings in a confirmatory manner, while cross-loadings are targeted to be as close to zero as possible.

The measurement models were estimated using the robust weighted least square estimator using diagonal weight matrices (WLSMV) to take into account the ordered-categorical ratings scales underlying the various indicators used in these models. The choice to rely on WLSMV estimation is linked to the fact that this estimator is more suited to the ordered-categorical nature of the 4-point Likert scales used in the present study than traditional maximum likelihood (ML) estimation or robust alternatives (MLR) (Finney & DiStefano, 2013). Indeed, ML/MLR estimation assumes that the underlying response scale is continuous, and that responses are normally distributed. Although ML/MLR is to some extent robust to non-normality, assumptions of underlying continuity are harder to approximate when few response categories are used (simulations studies suggest five answer categories or less as the point at which WSLMV tends to outperform ML/MLR), or when responses categories follow asymmetric thresholds (as is the case in this study). In these conditions, WLSMV estimation has been found to outperform ML/MLR estimation (Bandalos, 2014; Beauducel & Herzberg, 2006; Finney & DiStephano, 2013; Flora & Curran, 2004; Lei, 2009; Lubke & Muthén, 2004; Rhemtulla, Brosseau-Liard, & Savalei, 2012).

Before saving the factor scores for our latent profile analyses, we verified that the measurement model operated in the same manner across gender, through tests of measurement invariance (Millsap, 2011): (1) configural invariance, (2) weak invariance (loadings), (3) strong invariance (loadings and thresholds), (4) strict invariance (loadings, thresholds and uniquenesses); (5) invariance of the latent variance-covariance matrix (loadings, thresholds, uniquenesses, and latent variances and covariances); (6) latent means invariance (loadings, thresholds, uniquenesses, latent variances and covariances, and latent means). In models relying on WLSMV estimation, thresholds replace intercepts and reflect the points at which responses change from one category to another.

Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications (e.g., Marsh, Hau, & Grayson, 2005), we relied on goodness-of-fit indices to describe the fit of the alternative models (Hu & Bentler, 1999; Yu, 2002): the comparative fit index (CFI), the Tucker-Lewis index (TLI), as well as the root mean square error of approximation (RMSEA) and its 90% confidence interval. Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA respectively support acceptable and excellent model fit. Like the chi square, chi square difference tests present a known sensitivity to sample size and minor model misspecifications so that recent studies suggest complementing this information with changes in CFIs and RMSEAs (Chen, 2007; Cheung & Rensvold, 2002) in the context of tests of measurement invariance. A ΔCFI of .010

or less and a ΔRMSEA of .015 or less between a more restricted model and the preceding one indicate that the invariance hypothesis should not be rejected. It should be noted that with WLSMV, chi-square values are not exact, but rather adjusted or "*estimated*" to obtain a correct *p*-value. This explains why χ^2 and CFI values can be non-monotonic with model complexity. This specificity is also important for the WLSMV χ^2 difference tests, which need to be conducted via Mplus' DIFFTEST function (MD$\Delta\chi^2$; Asparouhov, & Muthén, 2006).

The results from the achievement goal models are reported at the top of the supplementary Table S1. These results clearly support the a priori models of configural invariance. The results also supported the strong, strict, correlated uniquenesses, latent variance-covariance and latent means invariance of the model. To ensure that the latent profiles estimated were based on fully comparable measures of outcomes across gender, the factor scores used in the main analyses were saved, from the most invariant model. Although only strict measurement invariance is required to ensure that measurement of the constructs remains equivalent across gender for models based on factor scores (e.g., Millsap, 2011), there are advantages to saving factors scores from a model of complete measurement invariance for use in latent profile analyses. Indeed, saving factor scores based on a measurement model in which both the variances and the latent means are invariant (i.e., respectively constrained to take a value of 1 and 0 in both groups) provides scores on profile indicators that can be readily interpreted in standardized terms as deviation from the grand mean expressed in SD units. Results from this final model for the achievement goals are presented in tables S2. Measurement models for predictors and outcomes were also adequate and fully invariant across gender (see Table S1). Correlations among all factors considered in the current study are reported in Table S3.

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Table S1. *Goodness-of-Fit Statistics of the Measurement Models*

Description	$\chi^2(df)$	CFI	TLI	RMSEA	90% CI	MD $\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Achievement Goals (ISM)									
Total	2813.406*(587)	.980	.969	.022	[.021, .023]	–	–	–	–
Males	1801.339*(587)	.988	.982	.022	[.021, .023]	–	–	–	–
Females	1723.201*(587)	.982	.973	.023	[.022, .024]	–	–	–	–
Configural Invariance (same model freely estimated across gender, no equality constraint)	3417.253*(1174)	.986	.979	.022	[.021, .023]	–	–	–	–
Loadings (Weak) Invariance	3010.319*(1454)	.990	.988	.017	[.016, .017]	553.308*(280)	+.004	+.009	-.005
Thresholds (Strong) Invariance	3104.206*(1532)	.990	.989	.016	[.015, .017]	310.246*(78)	.000	+.001	-.001
Uniquenesses (Strict) Invariance	3074.468*(1575)	.991	.989	.016	[.015, .016]	179.324*(43)	+.001	.000	.000
Latent Variance-Covariance Invariance	3634.881*(1611)	.987	.986	.018	[.017, .019]	326.204*(36)	-.004	-.003	.002
Latent Means Invariance	3647.857*(1619)	.987	.986	.018	[.017, .019]	66.812*(8)	.000	.000	.000
Predictors									
Total	497.172*(133)	.992	.981	.019	[.017, .021]	–	–	–	–
Males	395.424*(133)	.994	.986	.022	[.019, .024]	–	–	–	–
Females	302.274*(133)	.993	.985	.016	[.016, .022]	–	–	–	–
Configural Invariance (same model freely estimated across gender, no equality constraint)	708.161*(266)	.993	.984	.021	[.019, .023]	–	–	–	–
Loadings (Weak) Invariance	748.921*(401)	.994	.992	.015	[.013, .017]	230.674*(135)	+.001	+.008	-.006
Thresholds (Strong) Invariance	765.497*(435)	.995	.993	.014	[.012, .016]	67.650*(34)	+.001	+.001	-.001
Uniquenesses (Strict) Invariance	803.802*(469)	.995	.993	.014	[.012, .015]	90.058*(34)	.000	.000	.000
Correlation Uniqueness Invariance	809.144*(473)	.995	.993	.014	[.012, .015]	13.495*(4)	.000	.000	.000
Latent Variance-Covariance Invariance	1469.896*(501)	.985	.982	.022	[.021, .024]	309.059*(28)	-.010	-.011	+.008
Latent Means Invariance	1418.805*(508)	.986	.983	.021	[.019, .023]	50.578*(7)	+.001	+.001	-.001
Outcomes									
Total	1243.259*(223)	.986	.973	.025	[.024, .027]	–	–	–	–
Males	832.765*(223)	.991	.982	.027	[.025, .029]	–	–	–	–
Females	764.379*(223)	.991	.983	.027	[.025, .029]	–	–	–	–
Configural Invariance (same model freely estimated across gender, no equality constraint)	1538.834*(446)	.991	.982	.026	[.025, .028]	–	–	–	–
Loadings (Weak) Invariance	1265.141*(662)	.995	.993	.017	[.016, .018]	293.793*(176)	+.004	+.011	-.009
Thresholds (Strong) Invariance	1316.723*(674)	.995	.993	.016	[.015, .018]	236.919*(52)	.000	.000	-.001
Uniquenesses (Strict) Invariance	1550.272*(699)	.993	.991	.018	[.017, .020]	406.937*(25)	-.002	-.002	+.002
Latent Variance-Covariance Invariance	1700.829*(735)	.992	.991	.019	[.018, .020]	239.906*(36)	-.001	.000	+.001
Latent Means Invariance	1685.738*(743)	.992	.991	.019	[.018, .020]	36.149*(8)	.000	.000	.000

Note. *$p < .01$; χ^2: Chi-square; *df*: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval of the RMSEA; MD $\Delta\chi^2$: Chi-square difference tests.

Table S2
Standardized Parameter Estimates from the Fully Invariant Measurement Model for the Achievement Goals

	Loading (λ)	Uniqueness (δ)
TASK1	.446	.585
TASK2	.739	.334
TASK3	.827	.189
TASK4	.602	.372
EFFORT1	.291	.478
EFFORT2	.675	.295
EFFORT3	.633	.305
EFFORT4	.737	.394
EFFORT5	.917	.239
EFFORT6	.784	.319
EFFORT7	.546	.380
COMP1	.868	.284
COMP2	.924	.211
COMP3	.723	.380
COMP4	.555	.410
COMP5	.608	.309
COMP6	.387	.487
SOCPO1	.647	.345
SOCPO2	.268	.585
SOCPO3	.899	.235
SOCPO4	.912	.139
SOCPO5	.537	.342
SOCPO6	.906	.148
AFFIL1	.303	.424
AFFIL2	.600	.350
AFFIL3	.567	.339
SOCON1	.520	.297
SOCON2	.714	.292
SOCON3	.642	.365
SOCON4	.733	.286
SOCON5	.440	.581
PRAISE1	.921	.132
PRAISE2	.859	.196
PRAISE3	.668	.221
PRAISE4	.734	.248
PRAISE5	.556	.403
TOKEN1	.529	.332
TOKEN2	.757	.260
TOKEN3	.987	.168
TOKEN4	.702	.382
TOKEN5	.515	.314
TOKEN6	.826	.362
TOKEN7	.751	.188

Note. All loadings and uniquenesses are significant ($p < .01$). TASK = Task involvement; EFFO = Effort; COMP = Competition; SPOW = Social power; AFFI = Affiliation; SCON = Social concern; PRAIS = praise; TOKEN = Token rewards.

Table S3

Standardized Factor Correlations

	TASK	EFFO	COMP	SPOW	AFFI	SCON	PRAIS	TOKEN	SCVAL	AFSC	PPEER	NPEER
TASK	-											
EFFO	.570**	-										
COMP	.275**	.451**	-									
SPOW	-.033	.394**	.635**	-								
AFFI	.370**	.391**	.212**	.232**	-							
SCON	.246**	.367**	.079**	.264**	.443**	-						
PRAIS	.392**	.494**	.611**	.512**	.439**	.335**	-					
TOKEN	.005	.300**	.557**	.604**	.223**	.186**	.625**	-				
SCVAL	.459**	.432**	.421**	.241**	.332**	.186**	.473**	.293**	-			
AFSC	.404**	.604**	.354**	.362**	.373**	.376**	.446**	.286**	.512**	-		
PPEER	.414**	.290**	.095**	-.025	.260**	.185**	.222**	-.055*	.395**	.281**	-	
NPEER	-.349**	-.084**	.072**	.243**	-.126**	-.011	-.012	.274**	-.173**	-.029	-.611**	-
PPAR	.298**	.353**	.296**	.246**	.256**	.199**	.326**	.220**	.464**	.405**	.338**	-.097**
NPAR	-.339**	-.085**	.045	.217**	-.115**	-.006	-.026	.242**	-.172**	-.030	-.566**	.847**
TEASU	.201**	.416**	.361**	.395**	.269**	.276**	.428**	.357**	.447**	.511**	.194**	.097**
GFAME	.085**	.217**	.316**	.306**	.113**	.095**	.253**	.234**	.166**	.194**	.042**	.023
GCARE	.293**	.178**	.172**	.054**	.183**	.110**	.222**	.075**	.292**	.161**	.209**	-.180**
GWEAL	.168**	.095**	.250**	.114**	.110**	.039*	.221**	.192**	.269**	.094**	.078**	-.045**
GFAMI	.264**	.194**	.169**	.092**	.193**	.155**	.211**	.080**	.254**	.182**	.189**	-.152**
GSOCI	.205**	.310**	.224**	.213**	.196**	.179**	.246**	.153**	.212**	.256**	.158**	-.083**
PERSE	.169**	.385**	.217**	.211**	.161**	.181**	.189**	.106**	.171**	.311**	.135**	-.053*
DEEP	.197**	.370**	.195**	.216**	.193**	.224**	.233**	.141**	.185**	.314**	.134**	-.031
SURF	-.095**	-.001	.105**	.142**	.011	.043**	.093**	.215**	.030*	.001	-.159**	.218**

Note. *$p < .05$; **$p < .01$; TASK = Task involvement; EFFO = Effort; COMP = Competition; SPOW = Social power; AFFI = Affiliation; SCON = Social concern; PRAIS = praise; TOKEN = Token rewards; SCVAL = School valuing; AFSC = Affect toward school; PPEER = Positive influence by peers; NPEER = Negative influence by peers; PPAR = Support from parents; NPAR = Negative influence by parents; TEASU = Support from teachers; GFAME = Fame goals; GCARE = Career goals; GWEAL = Wealth goals; GFAMI = Family goals; GSOCI = Society goals; PERSE = Task perseverance; DEEP = Deep learning; SURF = Surface learning.

Table S3 (continued)

	PPAR	NPAR	TEASU	GFAME	GCARE	GWEAL	GFAMI	GSOCI	PERSE	DEEP
PPAR	-									
NPAR	-.121**	-								
TEASU	.602**	.108**	-							
GFAME	.164**	.026	.201**	-						
GCARE	.159**	-.181**	.114**	.257**	-					
GWEAL	.111**	-.054**	.110**	.352**	.624**	-				
GFAMI	.152**	-.142**	.127**	.261**	.678**	.534**	-			
GSOCI	.195**	-.077**	.205**	.518**	.413**	.336**	.496**	-		
PERSE	.215**	-.053*	.245**	.269**	.170**	.091**	.189**	.312**	-	
DEEP	.184**	-.027	.236**	.305**	.219**	.141**	.250**	.405**	.457**	-
SURF	-.016	.196**	.038*	.176**	.036*	.175**	.041*	.079**	.068*	.243**

Table S4.

Goodness-of-Fit Results from the Latent Profile/Factor Mixture Analyses (With the Estimation of a Global Motivation Factor)

Model	LL	#fp	Scaling	AIC	CAIC	BIC	SABIC	Entropy	aLMR
Male (n=4221)									
1 profile	-40955.294	24	3.1303	81958.588	82134.936	82110.936	82034.674	Na	Na
2 profile	-39629.294	33	2.5391	79324.588	79567.066	79534.066	79429.206	.717	.333
3 profile	-39197.416	42	2.338	78478.832	78787.441	78745.441	78611.982	.768	≤.001
4 profile	-38901.727	51	2.249	77905.455	78280.194	78229.194	78067.137	.713	≤.001
5 profile	-38689.255	60	2.4078	77498.509	77939.379	77879.379	77688.724	.749	≤.001
6 profile	-38501.697	69	2.6811	77141.395	77648.395	77579.395	77360.142	.765	≤.001
7 profile	-38349.467	78	2.3819	76854.934	77428.065	77350.065	77102.213	.782	≤.001
Female (n=3627)									
1 profile	-33889.177	24	4.0777	67826.355	67999.063	67975.063	67898.803	Na	Na
2 profile	-32878.264	33	3.7518	65822.528	66060.001	66027.001	65922.143	.678	≤.001
3 profile	-32475.392	42	3.1308	65034.783	65337.022	65295.022	65161.567	.720	≤.001
4 profile	-32245.75	51	3.1575	64593.500	64960.504	64909.504	64747.452	.710	≤.001
5 profile	-32049.179	60	2.773	64218.357	64650.127	64590.127	64399.477	.703	≤.001
6 profile	-31930.482	69	2.5986	63998.965	64495.500	64426.500	64207.252	.709	≤.001
7 profile	-31800.921	78	2.3638	63757.841	64319.142	64241.142	63993.297	.747	≤.001

Note. These analyses are all based on a factor mixture approach to latent profile analyses, including a class-invariant latent factor controlling for global levels of motivation; LL: Model LogLikelihood; #fp: Number of free parameters; Scaling = scaling factor associated with MLR loglikelihood estimates; AIC: Akaïke Information Criteria; CAIC: Constant AIC; BIC: Bayesian Information Criteria; SABIC: Sample-Size adjusted BIC; aLMR: Adjusted Lo-Mendell-Rubin likelihood ratio test; *: $p \leq .01$.

Supplementary Table S5

Results from the Latent Profiles Preliminary Analyses (Without the Estimation of a Global Motivation Factor)

Model	LL	#fp	Scaling	AIC	CAIC	BIC	SABIC	Entropy	aLMR
Male (n=4221)									
1 profile	-46751.000	16	4.4657	93534.001	93651.566	93635.566	93584.725	Na	Na
2 profile	-43730.206	25	3.5470	87510.413	87694.109	87669.109	87589.669	0.757	0.3332
3 profile	-42147.653	34	3.3465	84363.307	84613.133	84579.133	84471.095	0.841	0.2926
4 profile	-41243.617	43	3.0359	82573.235	82889.192	82846.192	82709.556	0.856	≤0.001
5 profile	-40594.930	52	4.0868	81293.859	81675.946	81623.946	81458.712	0.823	0.1313
6 profile	-40111.792	61	2.3758	80345.583	80793.801	80732.801	80538.968	0.813	0.0071
7 profile	-39690.088	70	2.3092	79520.176	80034.524	79964.524	79742.093	0.831	≤0.001
Female (n=3627)									
1 profile	-37229.569	16	4.9274	74491.138	74606.276	74590.276	74539.436	Na	Na
2 profile	-35193.775	25	4.4079	70437.549	70617.453	70592.453	70513.016	0.743	0.3179
3 profile	-34347.97	34	3.3797	68763.941	69008.610	68974.61	68866.575	0.802	≤0.001
4 profile	-33852.12	43	3.1476	67790.241	68099.676	68056.676	67920.043	0.744	≤0.001
5 profile	-33503.489	52	3.3415	67110.977	67485.178	67433.178	67267.948	0.770	≤0.001
6 profile	-33158.346	61	3.1420	66438.693	66877.659	66816.659	66622.831	0.766	≤0.001
7 profile	-32895.091	70	2.5893	65930.183	66433.914	66363.914	66141.489	0.787	≤0.001

Note. These analyses are all based on a factor mixture approach to latent profile analyses, including a class-invariant latent factor controlling for global levels of motivation; LL: Model LogLikelihood; #fp: Number of free parameters; Scaling = scaling factor associated with MLR loglikelihood estimates; AIC: Akaïke Information Criteria; CAIC: Constant AIC; BIC: Bayesian Information Criteria; SABIC: Sample-Size adjusted BIC; aLMR: Adjusted Lo-Mendell-Rubin likelihood ratio test; *: $p \leq .01$.

Table S6

Detailed Results from the Final LPA Solution of Partial Dispersion Similarity.

	Profile 1	Profile 2	Profile 3
Achievement Goal	Mean (CI)	Mean (CI)	Mean (CI)
Task involvement	0.766 (0.624; 0.907)	0.099 (-0.119; 0.317)	0.899 (0.745; 1.054)
Effort	0.269 (0.052; 0.485)	-0.046 (-0.167; 0.076)	0.531 (0.360; 0.703)
Competition	0.861 (0.742; 0.980)	-0.004 (-0.160; 0.152)	-0.483 (-0.645; -0.321)
Social power	-0.146 (-0.365; 0.073)	0.075 (-0.087; 0.237)	-0.589 (-0.727; -0.451)
Affiliation	-0.403 (-0.568; -0.237)	0.163 (-0.028; 0.354)	0.558 (0.416; 0.699)
Social concern	-0.875 (-1.076; -0.673)	0.171 (-0.046; 0.387)	0.553 (0.455; 0.650)
Praise	0.292 (0.064; 0.521)	0.149 (0.036; 0.263)	0.006 (-0.126; 0.138)
Token rewards	-0.040 (-0.296; 0.215)	0.159 (0.004; 0.315)	-0.633 (-0.783; -0.482)

	Profile 4		Profile 5	
	Males	Females	Males	Females
	Mean (CI)	Mean (CI)	Mean (CI)	Mean (CI)
Task involvement	-0.806 (-0.936; -0.676)	-0.909 (-1.070; -0.747)	0.715 (0.506; 0.923)	-0.316 (-0.534; -0.098)
Effort	-0.375 (-0.48; -0.271)	-0.421 (-0.539; -0.302)	0.694 (0.506; 0.883)	-0.231 (-0.351; -0.110)
Competition	0.132 (0.037; 0.227)	0.001 (-0.110; 0.111)	0.226 (-0.125; 0.577)	-0.287 (-0.397; -0.178)
Social power	0.447 (0.282; 0.611)	0.569 (0.432; 0.706)	-0.115 (-0.526; 0.296)	-0.080 (-0.144; -0.016)
Affiliation	-0.326 (-0.398; -0.255)	-0.403 (-0.489; -0.317)	-0.188 (-0.628; 0.252)	-0.143 (-0.222; -0.064)
Social concern	-0.272 (-0.353; -0.192)	-0.288 (-0.355; -0.221)	0.020 (-0.815; 0.855)	-0.111 (-0.216; -0.005)
Praise	-0.213 (-0.305; -0.121)	-0.244 (-0.360; -0.127)	-0.920 (-1.153; -0.688)	-0.150 (-0.309; 0.010)
Token rewards	0.314 (0.189; 0.439)	0.308 (0.149; 0.468)	-1.195 (-1.482; -0.909)	-0.002 (-0.068; 0.064)

Note. These analyses are all based on a factor mixture approach to latent profile analyses, including a class-invariant latent factor controlling for global levels of motivation. Profile 1 = *Mastery-Competition Oriented*; Profile 2 = *Moderately Motivated*; Profile 3 = *Mastery-Socially Oriented*; Profile 4 = *Social Power and Rewards Oriented*; Profile 5 for Males = *Mastery Oriented*; Profile 5 for Females = *Moderately Unmotivated*.

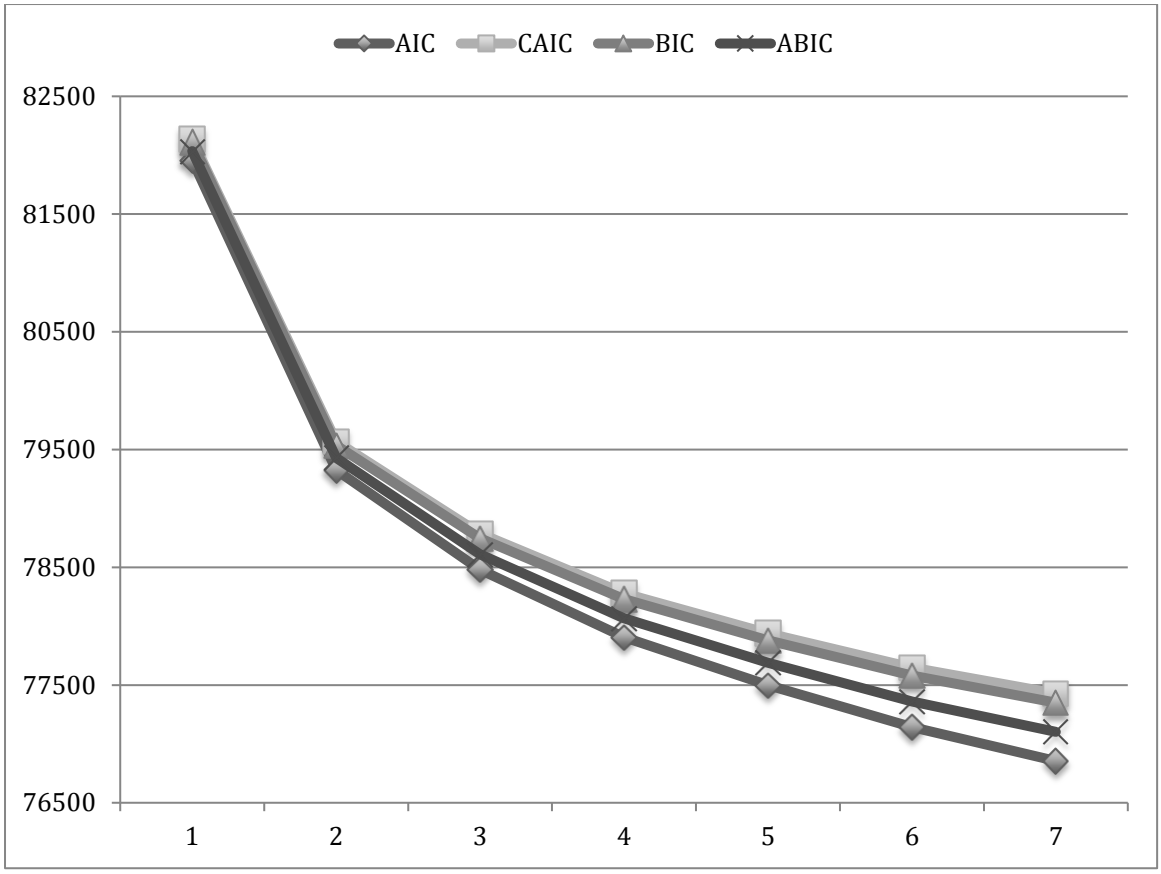

Figure S1. Elbow Plot for the Latent Profile Analyses (Males).

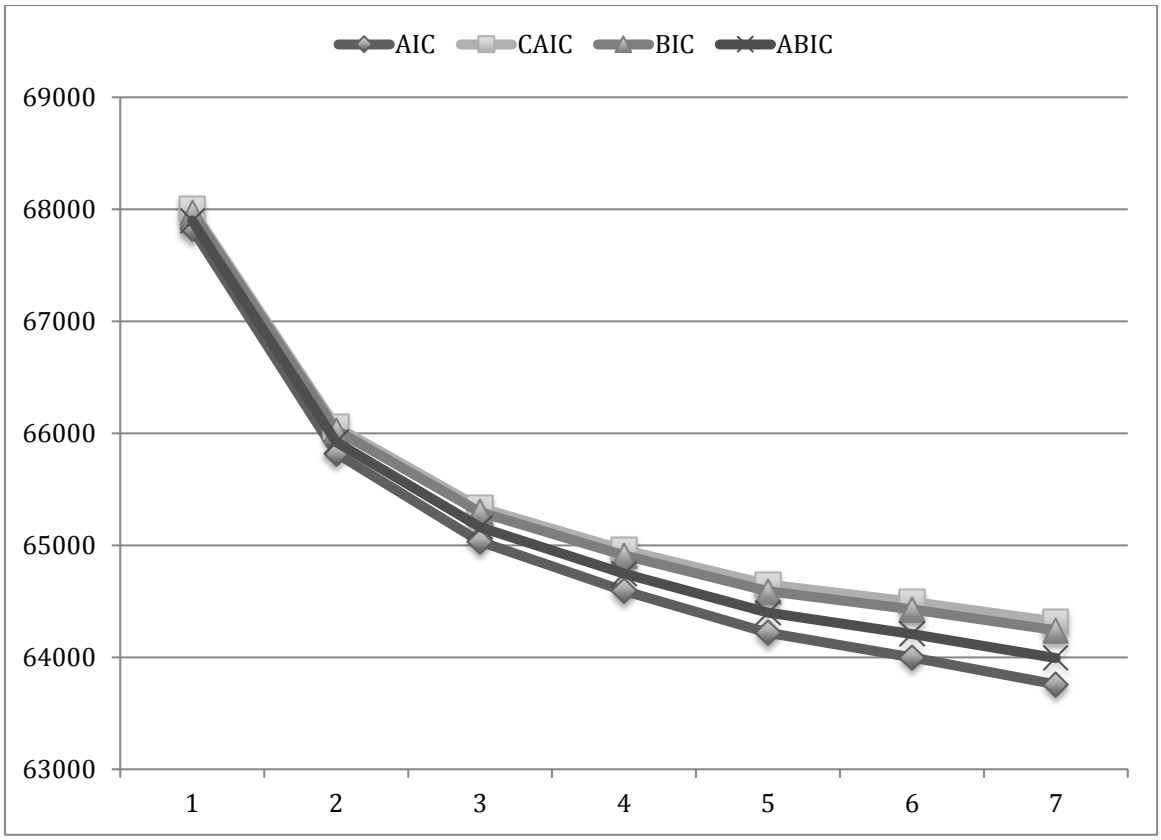

Figure S2. Elbow Plot for the Latent Profile Analyses (Females).

5-Class Latent Profile/Factor Mixture Analysis (Males)

```
! In all input files, statements preceded by "!" are annotations.
! Use the following statement to identify the data set. Here, the data set is labelled FSCORES
        HK.dat.
DATA: FILE IS FSCORES HK.dat;
! The variables names function identifies all variables in the data set, in order of appearance,
! whereas the usevariable command identifies the variables used in the analysis.
VARIABLE:
NAME = ID TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN GENDER
SCHOOLCODE VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER
FGFAME3 FGCAR3 FGWEAL3 FGFAMI3 FGSOC3 PERS3 DEEP3 SURF3;
USEVARIABLES = TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN;
! The following identifies the code for missing data
MISSING are all *;
! The following identifies the unique identifier for participants
IDVARIABLE = ID;
! The following identifies the subsample from which the participants are taken.
! In this case, the Males subsample (eq signifies :equal).
SUBPOPULATION is (GENDER eq 1);
! The following identifies that the data where nested in various schools.
CLUSTER = SCHOOLCODE;
! The following identifies the number of latent profiles requested in the analysis.
CLASSES = c (5);
! The following "Complex" addition is to correct the standard errors and chi-square test of
model fit that take into account that the data are nested.
TYPE = MIXTURE COMPLEX;
ESTIMATOR = MLR;
! The following set up is to estimate the model using 5000 starts values, 200 final stage
optimizations, and 100 iterations.
STARTS = 5000 200; STITERATIONS = 100;
! In this input, the overall model statement defines sections that are common across profiles.
! Here, we rely on a factor mixture approach including the estimation of a continuous global
latent
! factor to extract the level of variance that is shared across indicators. This factor (FG) is
specified
! as invariant and only in the %Overall% section of the model. For identification purposes,
all
! intercepts (corresponding to the means of the profile indicators) and loadings are freely
estimated,
! and the means and variance of this factor are respectively constrained to 0 and 1.
! The %c#1% to %c#5% sections are class-specific statement to specify which parts are
! freely estimated in each profile. Indicators' means (using []) are freely estimated in all
profiles
MODEL:
%OVERALL%
FG BY TASK* EFFO COMP SOCP AFFL SCRN PRSE TKEN;
FG@1; [FG@0];
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN];
%c#1%
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN];
```

```
%c#2%
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN];
%c#3%
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN];
%c#4%
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN];
%c#5%
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN];
! Specific sections of output are requested. TECH11 estimates LMR, and TECH14 estimates
BLRT.
OUTPUT:  STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

Configural Similarity Model for a Latent Profile/Factor Mixture Analysis

```
! Annotations only focus on functions not previously defined
DATA: FILE IS FSCORES HK.dat;
VARIABLE:
NAME = ID TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN GENDER
SCHOOLCODE VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER
FGFAME3 FGCAR3 FGWEAL3 FGFAMI3 FGSOC3 PERS3 DEEP3 SURF3;
USEVARIABLES = TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN;
MISSING are all *; IDVARIABLE = ID; CLUSTER = SCHOOLCODE;
! The following command is used to define a new grouping variable and its level. Here, the
label used ! is cg and the number 1 to 2 represent each gender.
KNOWNCLASS = cg (GENDER = 1 GENDER = 2);
! The mixture model will now consider that there are two latent grouping variables cg(2),
! with 5 profiles c (5).
CLASSES = cg (2) c (5);
ANALYSIS:
TYPE = MIXTURE COMPLEX; ESTIMATOR = MLR;
STARTS = 10000 500; STITERATIONS = 1000;
! The %OVERALL% section of the model section is used to indicate that the class sizes are
freely
! estimated across gender using the ON function (reflecting regressions) indicating that
profile
! membership is conditional on gender.
! Only k-1statements are required (i.e., 4 for a 5-profile model). Then, profile-specific
statements now
! need to be defined using a combination of both the known classes CG and the estimated
classes C.
! Labels in parentheses identify parameters that are estimated to be equal across groups.
! Here, even though all parameters are labeled, none of these labels are share between
groups,
! so that the means and variances are freely estimated in all combinations of profiles and
gender.
! Lists of constraints (e.g., mmale1-mmale8) apply to the parameters in order of appearance
! (e.g., mmale1 applies to TASK, mmale2 to EFFO, mmale3 to COMP and so on).
Model:
%OVERALL%
c#1 on cg#1; c#2 on cg#1; c#3 on cg#1; c#4 on cg#1;
FG BY TASK* EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN;
FG@1;
[FG@0];
%cg#1.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN](mmale1-mmale8);
TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN(vmale1-vmale8);
%cg#1.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN](mmale9-mmale16);
TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN(vmale1-vmale8);
```

```
%cg#1.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale25-mmale32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale33-mmale40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem1-mfem8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem9-mfem16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem17-mfem24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem25-mfem32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem33-mfem40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);OUTPUT:
STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

Structural Similarity Model for a Latent Profile/Factor Mixture Analysis

```
! Annotations only focus on functions not previously defined.
DATA: FILE IS FSCORES HK.dat;
VARIABLE:
NAME = ID TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN GENDER
SCHOOLCODE VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER
FGFAME3 FGCAR3 FGWEAL3 FGFAMI3 FGSOC3 PERS3 DEEP3 SURF3;
USEVARIABLES = TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN;
MISSING are all *; IDVARIABLE = ID; CLUSTER = SCHOOLCODE;
KNOWNCLASS = cg (GENDER = 1 GENDER = 2); CLASSES = cg (2) c (5);
ANALYSIS:
TYPE = MIXTURE COMPLEX; ESTIMATOR = MLR;
STARTS = 10000 500; STITERATIONS = 1000;
MODEL:
%OVERALL%
c#1 on cg#1; c#2 on cg#1; c#3 on cg#1; c#4 on cg#1;
FG BY TASK* EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN;
FG@1;
[FG@0];
! Labels in bold indicate newly imposed invariance constraints on means across gender.
%cg#1.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN](mmale1-mmale8);
TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN(vmale1-vmale8);
%cg#1.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN](mmale9-mmale16);
TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN(vmale1-vmale8);
%cg#1.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN](mmale17-mmale24);
TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN(vmale1-vmale8);
%cg#1.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN](mmale25-mmale32);
TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN(vmale1-vmale8);
%cg#1.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN](mmale33-mmale40);
TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN(vmale1-vmale8);
%cg#2.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN](mmale1-mmale8);
TASK  EFFO  COMP  SOCP  AFFL  SCRN  PRSE  TKEN(vfem1-vfem8);
```

%cg#2.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](**mmale9-mmale16**);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](**mmale17-mmale24**);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](**mmale25-mmale32**);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](**mmale33-mmale40**);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
OUTPUT: STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;

Partial Structural Similarity Model for a Latent Profile/Factor Mixture Analysis

```
! Annotations only focus on functions not previously defined.
DATA: FILE IS FSCORES HK.dat;
VARIABLE:
NAME = ID TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN GENDER
SCHOOLCODE VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER
FGFAME3 FGCAR3 FGWEAL3 FGFAMI3 FGSOC3 PERS3 DEEP3 SURF3;
USEVARIABLES = TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN;
MISSING are all *; IDVARIABLE = ID; CLUSTER = SCHOOLCODE;
KNOWNCLASS = cg (GENDER = 1 GENDER = 2); CLASSES = cg (2) c (5);
ANALYSIS:
TYPE = MIXTURE COMPLEX; ESTIMATOR = MLR;
STARTS = 10000 500; STITERATIONS = 1000;
MODEL:
%OVERALL%
c#1 on cg#1; c#2 on cg#1; c#3 on cg#1; c#4 on cg#1;
FG BY TASK* EFFO COMP SOCP AFFL SCRN PRSE TKEN;
FG@1;
[FG@0];
! Labels in bold indicate newly released constraints on means across gender for the fourth
(c#4) and
! the fifth (c#5) profiles. Please note that we first tested a model releasing the constraint on
the fifth
! profile only, and then tested this model for which the constraints are released in both group.
%cg#1.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale25-mmale32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale33-mmale40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#1%
```

FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](**mfem25-mfem32**);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](**mfem33-mfem40**);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
OUTPUT: STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;

Dispersion Similarity Model for a Latent Profile/Factor Mixture Analysis

```
! Annotations only focus on functions not previously defined.
! This model builds from the model of partial structural similarity.
DATA: FILE IS FSCORES HK.dat;
VARIABLE:
NAME = ID TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN GENDER
SCHOOLCODE VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER
FGFAME3 FGCAR3 FGWEAL3 FGFAMI3 FGSOC3 PERS3 DEEP3 SURF3;
USEVARIABLES = TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN;
MISSING are all *; IDVARIABLE = ID; CLUSTER = SCHOOLCODE;
KNOWNCLASS = cg (GENDER = 1 GENDER = 2); CLASSES = cg (2) c (5);
ANALYSIS:
TYPE = MIXTURE COMPLEX; ESTIMATOR = MLR;
STARTS = 10000 500; STITERATIONS = 1000;
MODEL:
%OVERALL%
c#1 on cg#1; c#2 on cg#1; c#3 on cg#1; c#4 on cg#1;
FG BY TASK* EFFO COMP SOCP AFFL SCRN PRSE TKEN;
FG@1;
[FG@0];
! Labels in bold indicate newly imposed invariance constraints on variances across gender.
! In line with the means of the partial structural similarity model, we freely estimate the
variance
! for fifth profile (c#5) across gender.
%cg#1.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale25-mmale32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale33-mmale40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#1%
```

FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(**vmale1-vmale8**);
%cg#2.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(**vmale1-vmale8**);
%cg#2.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(**vmale1-vmale8**);
%cg#2.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem25-mfem32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem33-mfem40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
OUTPUT: STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;

Distribution Similarity Model for a Latent Profile/Factor Mixture Analysis

```
! Annotations only focus on functions not previously defined.
! The only difference between this model and the model of dispersion similarity one is that
! the command c#1 on cg#1; c#2 on cg#1; c#3 on cg#1; c#4 on cg#1 as been removed from
! the %OVERALL% section of the input to reflect the fact that the sizes of the profiles
! are no longer conditional on gender.
DATA: FILE IS FSCORES HK.dat;
VARIABLE:
NAME = ID TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN GENDER
SCHOOLCODE VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER
FGFAME3 FGCAR3 FGWEAL3 FGFAMI3 FGSOC3 PERS3 DEEP3 SURF3;
USEVARIABLES = TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN;
MISSING are all *; IDVARIABLE = ID; CLUSTER = SCHOOLCODE;
KNOWNCLASS = cg (GENDER = 1 GENDER = 2); CLASSES = cg (2) c (5);
ANALYSIS:
TYPE = MIXTURE COMPLEX; ESTIMATOR = MLR;
STARTS = 10000 500; STITERATIONS = 1000;
MODEL:
%OVERALL%
FG BY TASK* EFFO COMP SOCP AFFL SCRN PRSE TKEN;
FG@1;
[FG@0];
%cg#1.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale25-mmale32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale33-mmale40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
```

```
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem25-mfem32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem33-mfem40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

Latent Profile/Factor Mixture Analysis with Predictors Freely Estimated Across Gender.

```
! Annotations only focus on functions not previously defined.
! This model builds from the model of partial dispersion similarity.
! To ensure stability, starts values from the previously most invariant solution should be used.
DATA: FILE IS FSCORES HK.dat;
VARIABLE:
NAME = ID TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN GENDER
SCHOOLCODE VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER
FGFAME3 FGCAR3 FGWEAL3 FGFAMI3 FGSOC3 PERS3 DEEP3 SURF3;
! Predictors were added in the following statement.
USEVARIABLES = TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN VALUE
AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER;
MISSING are all *; IDVARIABLE = ID; CLUSTER = SCHOOLCODE;
KNOWNCLASS = cg (GENDER = 1 GENDER = 2); CLASSES = cg (2) c (5);
ANALYSIS:
TYPE = MIXTURE COMPLEX; ESTIMATOR = MLR;
STARTS = 10000 500; STITERATIONS = 1000;
! To ensure that the latent profile solution remains unchanged by the inclusion of predictors,
        starts
! values from the final retained model without covariates (predictors/outcomes) can be used
        and the
! random starts fixed to 0. STARTS = 0;
MODEL:
%OVERALL%
c#1 on cg#1; c#2 on cg#1; c#3 on cg#1; c#4 on cg#1;
FG BY TASK* EFFO COMP SOCP AFFL SCRN PRSE TKEN;
FG@1;
[FG@0];
! The following command was added to include the effect of covariates on profile
        memberships.
! To allow these effects to be freely estimated across gender, they need to be
! constrained to 0 in the %OVERALL% section, and freely estimated in each gender in a new
! section of the input specifically referring to CG. See all sections in bold.
c#1-c#4 ON VALUE@0 AFFECT@0 PEERPOS@0 PEERNEG@0 PARPOS@0
PARNEG@0 TEACHER@0;
%cg#1.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
```

```
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale25-mmale32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale33-mmale40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem25-mfem32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem33-mfem40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
MODEL cg:
%cg#1%
c#1-c#4 ON VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER;
%cg#2%
c#1-c#4 ON VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER;
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

Predictive Similarity Latent Profile/Factor Mixture Analysis

```
! Annotations only focus on functions not previously defined.
! This model is almost identical to the previous one.
! In order for the effects of the predictors to be constrained to invariance across gender, they
! simply need to be specified as freely estimated in the %OVERALL% section by adding the
        following
! command. The section added in the previous model, which was specific to gender groups,
        must
! also be removed.
DATA: FILE IS FSCORES HK.dat;
VARIABLE:
NAME = ID TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN GENDER
SCHOOLCODE VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER
FGFAME3 FGCAR3 FGWEAL3 FGFAMI3 FGSOC3 PERS3 DEEP3 SURF3;
! Predictors were added in the following statement.
USEVARIABLES = TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN VALUE
AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER;
MISSING are all *; IDVARIABLE = ID; CLUSTER = SCHOOLCODE;
KNOWNCLASS = cg (GENDER = 1 GENDER = 2); CLASSES = cg (2) c (5);
ANALYSIS:
TYPE = MIXTURE COMPLEX; ESTIMATOR = MLR;
STARTS = 10000 500; STITERATIONS = 1000;
! To ensure that the latent profile solution remains unchanged by the inclusion of predictors,
        starts
! values from the final retained model without covariates (predictors/outcomes) can be used
        and the
! random starts fixed to 0. STARTS = 0;
MODEL:
%OVERALL%
c#1 on cg#1; c#2 on cg#1; c#3 on cg#1; c#4 on cg#1;
FG BY TASK* EFFO COMP SOCP AFFL SCRN PRSE TKEN;
FG@1;
[FG@0];
c#1-c#4 ON VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER;
%cg#1.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#4%
```

```
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale25-mmale32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#1.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale33-mmale40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
%cg#2.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem25-mfem32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
%cg#2.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem33-mfem40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

Latent Profile/Factor Mixture Analysis with Outcomes Levels Freely Estimated Across Gender

```
! Annotations only focus on functions not previously defined.
! This model builds from the model of dispersion similarity.
! To ensure stability, starts values from the previously most invariant solution (partial
dispersion similarity) should be used.
DATA: FILE IS FSCORES HK.dat;
VARIABLE:
NAME = ID TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN GENDER
SCHOOLCODE VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER
FGFAME3 FGCAR3 FGWEAL3 FGFAMI3 FGSOC3 PERS3 DEEP3 SURF3;
! Outcomes were added in the following command.
USEVARIABLES = TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN FGFAME3
FGCAR3 FGWEAL3 FGFAMI3 FGSOC3 PERS3 DEEP3 SURF3;
MISSING are all *; IDVARIABLE = ID; CLUSTER = SCHOOLCODE;
KNOWNCLASS = cg (GENDER = 1 GENDER = 2); CLASSES = cg (2) c (5);
ANALYSIS:
TYPE = MIXTURE COMPLEX; ESTIMATOR = MLR;
STARTS = 10000 500; STITERATIONS = 1000;
! To ensure that the latent profile solution remains unchanged by the inclusion of predictors,
        starts
! values from the final retained model without covariates (predictors/outcomes) can be used
        and the
! random starts fixed to 0. STARTS = 0;
MODEL:
%OVERALL%
c#1 on cg#1; c#2 on cg#1; c#3 on cg#1; c#4 on cg#1;
FG BY TASK* EFFO COMP SOCP AFFL SCRN PRSE TKEN;
FG@1;
[FG@0];
! The following statements are added to request the free estimation of the distal outcome
means in all profiles for each gender group. We also use labels in parentheses to identify
these new parameters, which will then be used in a new MODEL CONSTRAINT section to
request tests of the significance of mean differences between profiles and gender groups. See
all sections in bold.
%cg#1.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa1); [FGCAR3](ba1); [FGWEAL3](ca1); [FGFAMI3](da1);
[FGSOC3](ea1);
[PERS3](fa1); [DEEP3](ga1); [SURF3](ha1);
%cg#1.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa2); [FGCAR3](ba2); [FGWEAL3](ca2); [FGFAMI3](da2);
[FGSOC3](ea2);
```

[PERS3](fa2); [DEEP3](ga2); [SURF3](ha2);
%cg#1.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa3); [FGCAR3](ba3); [FGWEAL3](ca3); [FGFAMI3](da3); [FGSOC3](ea3);
[PERS3](fa3); [DEEP3](ga3); [SURF3](ha3);
%cg#1.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale25-mmale32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa4); [FGCAR3](ba4); [FGWEAL3](ca4); [FGFAMI3](da4); [FGSOC3](ea4);
[PERS3](fa4); [DEEP3](ga4); [SURF3](ha4);
%cg#1.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale33-mmale40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa5); [FGCAR3](ba5); [FGWEAL3](ca5); [FGFAMI3](da5); [FGSOC3](ea5);
[PERS3](fa5); [DEEP3](ga5); [SURF3](ha5);
%cg#2.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](ab1); [FGCAR3](bb1); [FGWEAL3](cb1); [FGFAMI3](db1); [FGSOC3](eb1);
[PERS3](fb1); [DEEP3](gb1); [SURF3](hb1);
%cg#2.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](ab2); [FGCAR3](bb2); [FGWEAL3](cb2); [FGFAMI3](db2); [FGSOC3](eb2);
[PERS3](fb2); [DEEP3](gb2); [SURF3](hb2);
%cg#2.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](ab3); [FGCAR3](bb3); [FGWEAL3](cb3); [FGFAMI3](db3); [FGSOC3](eb3);
[PERS3](fb3); [DEEP3](gb3); [SURF3](hb3);
%cg#2.c#4%

FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem25-mfem32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
[FGFAME3](ab4); [FGCAR3](bb4); [FGWEAL3](cb4); [FGFAMI3](db4);
[FGSOC3](eb4);
[PERS3](fb4); [DEEP3](gb4); [SURF3](hb4);
%cg#2.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem33-mfem40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
[FGFAME3](ab5); [FGCAR3](bb5); [FGWEAL3](cb5); [FGFAMI3](db5);
[FGSOC3](eb5);
[PERS3](fb5); [DEEP3](gb5); [SURF3](hb5);
! New parameters are created using this function and reflect pairwise mean differences between
! profiles. So the first of those (yaa12) reflect the differences between the means of profiles 1 and 2 in ! the Male subsample.
! This will be included in the outputs as new parameters reflecting the significance of
! the differences between the means, without those parameters having an impact on the model.
! In the chosen labels:
! y = Intragroup comparison (between profiles).
! a to h (second parameter) = outcome identification.
! a or b (third parameter) = gender groups.
! 12 = comparison between profiles 1 and 2.
!!!!!!!!!!!!!!!!!!
!!!!!Males!!!!!!
!!!!!!!!!!!!!!!!!
NEW (yaa12);
yaa12 = aa1-aa2;
NEW (yaa13);
yaa13 = aa1-aa3;
NEW (yaa14);
yaa14 = aa1-aa4;
NEW (yaa15);
yaa15 = aa1-aa5;
NEW (yaa23);
yaa23 = aa2-aa3;
NEW (yaa24);
yaa24 = aa2-aa4;
NEW (yaa25);
yaa25 = aa2-aa5;
NEW (yaa34);
yaa34 = aa3-aa4;
NEW (yaa35);
yaa35 = aa3-aa5;
NEW (yaa45);
yaa45 = aa4-aa5;

```
NEW (yba12);
yba12 = ba1-ba2;
NEW (yba13);
yba13 = ba1-ba3;
NEW (yba14);
yba14 = ba1-ba4;
NEW (yba15);
yba15 = ba1-ba5;
NEW (yba23);
yba23 = ba2-ba3;
NEW (yba24);
yba24 = ba2-ba4;
NEW (yba25);
yba25 = ba2-ba5;
NEW (yba34);
yba34 = ba3-ba4;
NEW (yba35);
yba35 = ba3-ba5;
NEW (yba45);
yba45 = ba4-ba5;
NEW (yca12);
yca12 = ca1-ca2;
NEW (yca13);
yca13 = ca1-ca3;
NEW (yca14);
yca14 = ca1-ca4;
NEW (yca15);
yca15 = ca1-ca5;
NEW (yca23);
yca23 = ca2-ca3;
NEW (yca24);
yca24 = ca2-ca4;
NEW (yca25);
yca25 = ca2-ca5;
NEW (yca34);
yca34 = ca3-ca4;
NEW (yca35);
yca35 = ca3-ca5;
NEW (yca45);
yca45 = ca4-ca5;
NEW (yda12);
yda12 = da1-da2;
NEW (yda13);
yda13 = da1-da3;
NEW (yda14);
yda14 = da1-da4;
NEW (yda15);
yda15 = da1-da5;
NEW (yda23);
yda23 = da2-da3;
```

```
NEW (yda24);
yda24 = da2-da4;
NEW (yda25);
yda25 = da2-da5;
NEW (yda34);
yda34 = da3-da4;
NEW (yda35);
yda35 = da3-da5;
NEW (yda45);
yda45 = da4-da5;
NEW (yea12);
yea12 = ea1-ea2;
NEW (yea13);
yea13 = ea1-ea3;
NEW (yea14);
yea14 = ea1-ea4;
NEW (yea15);
yea15 = ea1-ea5;
NEW (yea23);
yea23 = ea2-ea3;
NEW (yea24);
yea24 = ea2-ea4;
NEW (yea25);
yea25 = ea2-ea5;
NEW (yea34);
yea34 = ea3-ea4;
NEW (yea35);
yea35 = ea3-ea5;
NEW (yea45);
yea45 = ea4-ea5;
NEW (yfa12);
yfa12 = fa1-fa2;
NEW (yfa13);
yfa13 = fa1-fa3;
NEW (yfa14);
yfa14 = fa1-fa4;
NEW (yfa15);
yfa15 = fa1-fa5;
NEW (yfa23);
yfa23 = fa2-fa3;
NEW (yfa24);
yfa24 = fa2-fa4;
NEW (yfa25);
yfa25 = fa2-fa5;
NEW (yfa34);
yfa34 = fa3-fa4;
NEW (yfa35);
yfa35 = fa3-fa5;
NEW (yfa45);
yfa45 = fa4-fa5;
```

```
NEW (yga12);
yga12 = ga1-ga2;
NEW (yga13);
yga13 = ga1-ga3;
NEW (yga14);
yga14 = ga1-ga4;
NEW (yga15);
yga15 = ga1-ga5;
NEW (yga23);
yga23 = ga2-ga3;
NEW (yga24);
yga24 = ga2-ga4;
NEW (yga25);
yga25 = ga2-ga5;
NEW (yga34);
yga34 = ga3-ga4;
NEW (yga35);
yga35 = ga3-ga5;
NEW (yga45);
yga45 = ga4-ga5;
NEW (yha12);
yha12 = ha1-ha2;
NEW (yha13);
yha13 = ha1-ha3;
NEW (yha14);
yha14 = ha1-ha4;
NEW (yha15);
yha15 = ha1-ha5;
NEW (yha23);
yha23 = ha2-ha3;
NEW (yha24);
yha24 = ha2-ha4;
NEW (yha25);
yha25 = ha2-ha5;
NEW (yha34);
yha34 = ha3-ha4;
NEW (yha35);
yha35 = ha3-ha5;
NEW (yha45);
yha45 = ha4-ha5;
!!!!!!!!!!!!!!!!!!!
!!! Females  !!!!
!!!!!!!!!!!!!!!!!!!
NEW (yab12);
yab12 = ab1-ab2;
NEW (yab13);
yab13 = ab1-ab3;
NEW (yab14);
yab14 = ab1-ab4;
NEW (yab15);
```

```
yab15 = ab1-ab5;
NEW (yab23);
yab23 = ab2-ab3;
NEW (yab24);
yab24 = ab2-ab4;
NEW (yab25);
yab25 = ab2-ab5;
NEW (yab34);
yab34 = ab3-ab4;
NEW (yab35);
yab35 = ab3-ab5;
NEW (yab45);
yab45 = ab4-ab5;
NEW (ybb12);
ybb12 = bb1-bb2;
NEW (ybb13);
ybb13 = bb1-bb3;
NEW (ybb14);
ybb14 = bb1-bb4;
NEW (ybb15);
ybb15 = bb1-bb5;
NEW (ybb23);
ybb23 = bb2-bb3;
NEW (ybb24);
ybb24 = bb2-bb4;
NEW (ybb25);
ybb25 = bb2-bb5;
NEW (ybb34);
ybb34 = bb3-bb4;
NEW (ybb35);
ybb35 = bb3-bb5;
NEW (ybb45);
ybb45 = bb4-bb5;
NEW (ycb12);
ycb12 = cb1-cb2;
NEW (ycb13);
ycb13 = cb1-cb3;
NEW (ycb14);
ycb14 = cb1-cb4;
NEW (ycb15);
ycb15 = cb1-cb5;
NEW (ycb23);
ycb23 = cb2-cb3;
NEW (ycb24);
ycb24 = cb2-cb4;
NEW (ycb25);
ycb25 = cb2-cb5;
NEW (ycb34);
ycb34 = cb3-cb4;
NEW (ycb35);
```

```
ycb35 = cb3-cb5;
NEW (ycb45);
ycb45 = cb4-cb5;
NEW (ydb12);
ydb12 = db1-db2;
NEW (ydb13);
ydb13 = db1-db3;
NEW (ydb14);
ydb14 = db1-db4;
NEW (ydb15);
ydb15 = db1-db5;
NEW (ydb23);
ydb23 = db2-db3;
NEW (ydb24);
ydb24 = db2-db4;
NEW (ydb25);
ydb25 = db2-db5;
NEW (ydb34);
ydb34 = db3-db4;
NEW (ydb35);
ydb35 = db3-db5;
NEW (ydb45);
ydb45 = db4-db5;
NEW (yeb12);
yeb12 = eb1-eb2;
NEW (yeb13);
yeb13 = eb1-eb3;
NEW (yeb14);
yeb14 = eb1-eb4;
NEW (yeb15);
yeb15 = eb1-eb5;
NEW (yeb23);
yeb23 = eb2-eb3;
NEW (yeb24);
yeb24 = eb2-eb4;
NEW (yeb25);
yeb25 = eb2-eb5;
NEW (yeb34);
yeb34 = eb3-eb4;
NEW (yeb35);
yeb35 = eb3-eb5;
NEW (yeb45);
yeb45 = eb4-eb5;
NEW (yfb12);
yfb12 = fb1-fb2;
NEW (yfb13);
yfb13 = fb1-fb3;
NEW (yfb14);
yfb14 = fb1-fb4;
NEW (yfb15);
```

```
yfb15 = fb1-fb5;
NEW (yfb23);
yfb23 = fb2-fb3;
NEW (yfb24);
yfb24 = fb2-fb4;
NEW (yfb25);
yfb25 = fb2-fb5;
NEW (yfb34);
yfb34 = fb3-fb4;
NEW (yfb35);
yfb35 = fb3-fb5;
NEW (yfb45);
yfb45 = fb4-fb5;
NEW (ygb12);
ygb12 = gb1-gb2;
NEW (ygb13);
ygb13 = gb1-gb3;
NEW (ygb14);
ygb14 = gb1-gb4;
NEW (ygb15);
ygb15 = gb1-gb5;
NEW (ygb23);
ygb23 = gb2-gb3;
NEW (ygb24);
ygb24 = gb2-gb4;
NEW (ygb25);
ygb25 = gb2-gb5;
NEW (ygb34);
ygb34 = gb3-gb4;
NEW (ygb35);
ygb35 = gb3-gb5;
NEW (ygb45);
ygb45 = gb4-gb5;
NEW (yhb12);
yhb12 = hb1-hb2;
NEW (yhb13);
yhb13 = hb1-hb3;
NEW (yhb14);
yhb14 = hb1-hb4;
NEW (yhb15);
yhb15 = hb1-hb5;
NEW (yhb23);
yhb23 = hb2-hb3;
NEW (yhb24);
yhb24 = hb2-hb4;
NEW (yhb25);
yhb25 = hb2-hb5;
NEW (yhb34);
yhb34 = hb3-hb4;
NEW (yhb35);
```

```
yhb35 = hb3-hb5;
NEW (yhb45);
yhb45 = hb4-hb5;
! w = Intergroup comparison (across gender)
! a to h (second parameter) = outcome identification.
! 11 = comparison between profile 1 males and profile 1 females
NEW (wa11);
wa11 = aa1-ab1;
NEW (wa22);
wa22= aa2-ab2;
NEW (wa33);
wa33= aa3-ab3;
NEW (wa44);
wa44= aa4-ab4;
NEW (wa55);
wa55= aa5-ab5;
NEW (wb11);
wb11 = ba1-bb1;
NEW (wb22);
wb22= ba2-bb2;
NEW (wb33);
wb33= ba3-bb3;
NEW (wb44);
wb44= ba4-bb4;
NEW (wb55);
wb55= ba5-bb5;
NEW (wc11);
wc11 = ca1-cb1;
NEW (wc22);
wc22= ca2-cb2;
NEW (wc33);
wc33= ca3-cb3;
NEW (wc44);
wc44= ca4-cb4;
NEW (wc55);
wc55= ca5-cb5;
NEW (wd11);
wd11 = da1-db1;
NEW (wd22);
wd22= da2-db2;
NEW (wd33);
wd33= da3-db3;
NEW (wd44);
wd44= da4-db4;
NEW (wd55);
wd55= da5-db5;
NEW (we11);
we11 = ea1-eb1;
NEW (we22);
we22= ea2-eb2;
```

```
NEW (we33);
we33= ea3-eb3;
NEW (we44);
we44= ea4-eb4;
NEW (we55);
we55= ea5-eb5;
NEW (wf11);
wf11 = fa1-fb1;
NEW (wf22);
wf22= fa2-fb2;
NEW (wf33);
wf33= fa3-fb3;
NEW (wf44);
wf44= fa4-fb4;
NEW (wf55);
wf55= fa5-fb5;
NEW (wg11);
wg11= ga1-gb1;
NEW (wg22);
wg22= ga2-gb2;
NEW (wg33);
wg33= ga3-gb3;
NEW (wg44);
wg44= ga4-gb4;
NEW (wg55);
wg55= ga5-gb5;
NEW (wh11);
wh11 = ha1-hb1;
NEW (wh22);
wh22= ha2-hb2;
NEW (wh33);
wh33= ha3-hb3;
NEW (wh44);
wh44= ha4-hb4;
NEW (wh55);
wh55= ha5-hb5;
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

Explanatory Similarity Latent Profile/Factor Mixture Analysis

```
! Annotations only focus on functions not previously defined.
! This model builds from the model of dispersion similarity.
! To ensure stability, starts values from the previously most invariant solution (partial
dispersion similarity) should be used.
DATA: FILE IS FSCORES HK.dat;
VARIABLE:
NAME = ID TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN GENDER
SCHOOLCODE VALUE AFFECT PEERPOS PEERNEG PARPOS PARNEG TEACHER
FGFAME3 FGCAR3 FGWEAL3 FGFAMI3 FGSOC3 PERS3 DEEP3 SURF3;
! Outcomes were added in the following command.
USEVARIABLES = TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN FGFAME3
FGCAR3 FGWEAL3 FGFAMI3 FGSOC3 PERS3 DEEP3 SURF3;
MISSING are all *; IDVARIABLE = ID; CLUSTER = SCHOOLCODE;
KNOWNCLASS = cg (GENDER = 1 GENDER = 2); CLASSES = cg (2) c (5);
ANALYSIS:
TYPE = MIXTURE COMPLEX; ESTIMATOR = MLR;
STARTS = 10000 500; STITERATIONS = 1000;
! To ensure that the latent profile solution remains unchanged by the inclusion of predictors,
        starts
! values from the final retained model without covariates (predictors/outcomes) can be used
        and the
! random starts fixed to 0. STARTS = 0;
MODEL:
MODEL:
%OVERALL%
c#1 on cg#1; c#2 on cg#1; c#3 on cg#1; c#4 on cg#1;
FG BY TASK* EFFO COMP SOCP AFFL SCRN PRSE TKEN;
FG@1;
[FG@0];
! This model is almost identical to the previous one except that the parameter labels are used
to
! constrain the outcome means to be invariant gender.
! As a result, less lines of code are required in the MODEL CONSTRAINT section.
! See all sections in bold.
%cg#1.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa1); [FGCAR3](ba1); [FGWEAL3](ca1); [FGFAMI3](da1); [FGSOC3](ea1);
[PERS3](fa1); [DEEP3](ga1); [SURF3](ha1);
%cg#1.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa2); [FGCAR3](ba2); [FGWEAL3](ca2); [FGFAMI3](da2); [FGSOC3](ea2);
[PERS3](fa2); [DEEP3](ga2); [SURF3](ha2);
%cg#1.c#3%
```

FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa3); [FGCAR3](ba3); [FGWEAL3](ca3); [FGFAMI3](da3); [FGSOC3](ea3);
[PERS3](fa3); [DEEP3](ga3); [SURF3](ha3);
%cg#1.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale25-mmale32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa4); [FGCAR3](ba4); [FGWEAL3](ca4); [FGFAMI3](da4); [FGSOC3](ea4);
[PERS3](fa4); [DEEP3](ga4); [SURF3](ha4);
%cg#1.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale33-mmale40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa5); [FGCAR3](ba5); [FGWEAL3](ca5); [FGFAMI3](da5); [FGSOC3](ea5);
[PERS3](fa5); [DEEP3](ga5); [SURF3](ha5);
%cg#2.c#1%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale1-mmale8);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa1); [FGCAR3](ba1); [FGWEAL3](ca1); [FGFAMI3](da1);
[FGSOC3](ea1);
[PERS3](fa1); [DEEP3](ga1); [SURF3](ha1);
%cg#2.c#2%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale9-mmale16);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa2); [FGCAR3](ba2); [FGWEAL3](ca2); [FGFAMI3](da2);
[FGSOC3](ea2);
[PERS3](fa2); [DEEP3](ga2); [SURF3](ha2);
%cg#2.c#3%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mmale17-mmale24);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vmale1-vmale8);
[FGFAME3](aa3); [FGCAR3](ba3); [FGWEAL3](ca3); [FGFAMI3](da3);
[FGSOC3](ea3);
[PERS3](fa3); [DEEP3](ga3); [SURF3](ha3);
%cg#2.c#4%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem25-mfem32);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);

```
[FGFAME3](aa4); [FGCAR3](ba4); [FGWEAL3](ca4); [FGFAMI3](da4);
[FGSOC3](ea4);
[PERS3](fa4); [DEEP3](ga4); [SURF3](ha4);
%cg#2.c#5%
FG BY TASK*(fg1)
EFFO COMP SOCP AFFL SCRN PRSE TKEN(fg2-fg8);
[TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN](mfem33-mfem40);
TASK EFFO COMP SOCP AFFL SCRN PRSE TKEN(vfem1-vfem8);
[FGFAME3](aa5); [FGCAR3](ba5); [FGWEAL3](ca5); [FGFAMI3](da5);
        [FGSOC3](ea5);
[PERS3](fa5); [DEEP3](ga5); [SURF3](ha5);
MODEL CONSTRAINT:
! The model constraint function uses the labels used with the outcomes to request mean level
comparisons on the outcomes across profiles.
NEW (yaa12);
yaa12 = aa1-aa2;
NEW (yaa13);
yaa13 = aa1-aa3;
NEW (yaa14);
yaa14 = aa1-aa4;
NEW (yaa15);
yaa15 = aa1-aa5;
NEW (yaa23);
yaa23 = aa2-aa3;
NEW (yaa24);
yaa24 = aa2-aa4;
NEW (yaa25);
yaa25 = aa2-aa5;
NEW (yaa34);
yaa34 = aa3-aa4;
NEW (yaa35);
yaa35 = aa3-aa5;
NEW (yaa45);
yaa45 = aa4-aa5;
NEW (yba12);
yba12 = ba1-ba2;
NEW (yba13);
yba13 = ba1-ba3;
NEW (yba14);
yba14 = ba1-ba4;
NEW (yba15);
yba15 = ba1-ba5;
NEW (yba23);
yba23 = ba2-ba3;
NEW (yba24);
yba24 = ba2-ba4;
NEW (yba25);
yba25 = ba2-ba5;
NEW (yba34);
yba34 = ba3-ba4;
```

```
NEW (yba35);
yba35 = ba3-ba5;
NEW (yba45);
yba45 = ba4-ba5;
NEW (yca12);
yca12 = ca1-ca2;
NEW (yca13);
yca13 = ca1-ca3;
NEW (yca14);
yca14 = ca1-ca4;
NEW (yca15);
yca15 = ca1-ca5;
NEW (yca23);
yca23 = ca2-ca3;
NEW (yca24);
yca24 = ca2-ca4;
NEW (yca25);
yca25 = ca2-ca5;
NEW (yca34);
yca34 = ca3-ca4;
NEW (yca35);
yca35 = ca3-ca5;
NEW (yca45);
yca45 = ca4-ca5;
NEW (yda12);
yda12 = da1-da2;
NEW (yda13);
yda13 = da1-da3;
NEW (yda14);
yda14 = da1-da4;
NEW (yda15);
yda15 = da1-da5;
NEW (yda23);
yda23 = da2-da3;
NEW (yda24);
yda24 = da2-da4;
NEW (yda25);
yda25 = da2-da5;
NEW (yda34);
yda34 = da3-da4;
NEW (yda35);
yda35 = da3-da5;
NEW (yda45);
yda45 = da4-da5;
NEW (yea12);
yea12 = ea1-ea2;
NEW (yea13);
yea13 = ea1-ea3;
NEW (yea14);
yea14 = ea1-ea4;
```

```
NEW (yea15);
yea15 = ea1-ea5;
NEW (yea23);
yea23 = ea2-ea3;
NEW (yea24);
yea24 = ea2-ea4;
NEW (yea25);
yea25 = ea2-ea5;
NEW (yea34);
yea34 = ea3-ea4;
NEW (yea35);
yea35 = ea3-ea5;
NEW (yea45);
yea45 = ea4-ea5;
NEW (yfa12);
yfa12 = fa1-fa2;
NEW (yfa13);
yfa13 = fa1-fa3;
NEW (yfa14);
yfa14 = fa1-fa4;
NEW (yfa15);
yfa15 = fa1-fa5;
NEW (yfa23);
yfa23 = fa2-fa3;
NEW (yfa24);
yfa24 = fa2-fa4;
NEW (yfa25);
yfa25 = fa2-fa5;
NEW (yfa34);
yfa34 = fa3-fa4;
NEW (yfa35);
yfa35 = fa3-fa5;
NEW (yfa45);
yfa45 = fa4-fa5;
NEW (yga12);
yga12 = ga1-ga2;
NEW (yga13);
yga13 = ga1-ga3;
NEW (yga14);
yga14 = ga1-ga4;
NEW (yga15);
yga15 = ga1-ga5;
NEW (yga23);
yga23 = ga2-ga3;
NEW (yga24);
yga24 = ga2-ga4;
NEW (yga25);
yga25 = ga2-ga5;
NEW (yga34);
yga34 = ga3-ga4;
```

```
NEW (yga35);
yga35 = ga3-ga5;
NEW (yga45);
yga45 = ga4-ga5;
NEW (yha12);
yha12 = ha1-ha2;
NEW (yha13);
yha13 = ha1-ha3;
NEW (yha14);
yha14 = ha1-ha4;
NEW (yha15);
yha15 = ha1-ha5;
NEW (yha23);
yha23 = ha2-ha3;
NEW (yha24);
yha24 = ha2-ha4;
NEW (yha25);
yha25 = ha2-ha5;
NEW (yha34);
yha34 = ha3-ha4;
NEW (yha35);
yha35 = ha3-ha5;
NEW (yha45);
yha45 = ha4-ha5;
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```