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Middle school engagement profiles: Implications for motivation and achievement in science

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ABSTRACT

This study identified engagement profiles among middle school students ($N = 1125$) in science, based on a global, behavioral, cognitive, and affective dimensions of engagement. The relationships between engagement profiles and key motivation predictors (science achievement goal orientations and self-efficacy) and student achievement in science were also examined. Latent profile analysis revealed five distinct science engagement profiles, including Moderately Engaged, Moderately Disengaged, Disengaged, Behaviorally Engaged, and Behaviorally Disengaged. Controlling for grade, gender, and minority status, results showed that mastery orientation and self-efficacy significantly predicted the likelihood of membership in profiles characterized by higher engagement in science. As expected, the Moderately Engaged and Behaviorally Engaged profiles were associated with higher achievement in science, and the reverse pattern was found for the Moderately Disengaged and Disengaged profiles. Our results support the utility of examining multidimensional engagement profiles, and the implications of these profiles for students' motivation and learning in science are discussed.

1. Introduction

Engagement in school is critical to students' educational success, but unfortunately has shown to decline from the elementary through high school years (Eccles & Wang, 2012; Marks, 2000; Wigfield, Eccles, Schiefele, Roeser, & Davis-Kean, 2006). Particularly in science, drops in interest, motivation, and academic performance tend to be sharper compared to other subject areas during the pivotal middle school years (Morgan, Farkas, Hillemeier, & Maczuga, 2016; Quinn & Cooc, 2015; Wang & Fredricks, 2014). This is concerning because middle school is an important time in which students begin to formalize their attitudes toward academic activities and choices related to their future professional careers (Singh, Granville, & Dika, 2002; Tyson, Lee, Borman, & Hanson, 2007). Because it is malleable to changes in the learning context, a better understanding of student engagement has tremendous potential for informing educational interventions aimed at increasing learning and persistence in science (Azevedo, 2015; Christenson, Reschy, & Wylie, 2012; Eccles & Wang, 2012; Fredricks, Filsecker, & Lawson, 2016; Green, Martin, & Marsh, 2007).

Traditionally defined as the behavioral (e.g., completion of academic tasks, on-task behavior), affective (e.g., excitement, enjoyment in learning activities), and cognitive (e.g., mental effort to understand complex ideas) ways students connect to learning (Fredricks, Blumenfeld, & Paris, 2004; Lawson & Lawson, 2013), a large body of research shows that engagement is central to students' science learning and achievement. Student engagement in science supports more complex scientific ways of knowing and reasoning, deeper conceptual understanding (e.g., Azevedo, 2015; Greene, Azevedo, & Torney-Purta, 2008; Pugh, Linnenbrink-Garcia, Koskey, Stewart, & Manzey, 2010; Sinatra, Heddy, & Lombardi, 2015; Ryu & Lombardi, 2015), better grades and higher standardized test scores (Lee, Hayes, Seitz, DiStefano, & O'Connor, 2016; Greene, Miller, Crowson, Duke, & Akey, 2004; Midgley, Kaplan, & Middleton, 2001), and pursuit of advanced science classes and career choices in STEM fields (e.g., Lau & Roeser, 2002; Maltese & Tai, 2010; Wang & Holcombe, 2010). Active engagement in school is critical for students' learning and adjustment, and this may be particularly true in the domain of science where exploration and understanding of natural phenomena is achieved through hands-on investigation and collaborative sense-making (Fredricks, Wang, et al., 2016; Wang, Fredricks, Ye, Hofkens, & Linn, 2016).

Much of the existing literature assumes that individual students possess uniformly high or low levels of engagement in science. However, students may not be equally engaged across all three dimensions, but rather, the specific dimensions of engagement likely coexist within students at different levels (e.g., Wang & Peck, 2013). Person-centered approaches allow for the examination of profiles

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characterized by different configurations of engagement within individuals, that may in turn, be differentially associated with student outcomes. For example, students who are characterized by high levels of affective engagement, combined with low cognitive engagement may represent learners who are excited to participate in science but are not necessarily engaging in the learning tasks in a way that supports deep sense-making of the content. Students characterized by high behavioral and cognitive engagement, but low affective engagement, on the other hand may represent students who demonstrate on-task behaviors and academic achievement, but lack interest and emotional connection to science learning. These unique profiles are in turn, likely to be associated with different learning outcomes.

Few researchers have taken a person-centered approach to examine how students vary in their multivariate engagement profiles. The emerging engagement profile studies indicate that additional work in this area is warranted, but existing studies are largely focused on constructs outside of engagement (e.g., burnout), are conducted with high school or university students, and do not focus on engagement in a specific subject area (e.g., Tuominen-Soini & Salmela-Aro, 2014; van Rooij, Jansen, & van de Grift, 2017; Wang & Peck, 2013). Further work based on the well-established three-part engagement framework (Fredricks et al., 2004; Fredricks, Wang, et al., 2016), in other grade levels, specific subject areas, and among a diverse sample of students is needed. This line of inquiry is important to inform efforts to broaden participation in science by targeting different types of engagement needs, particularly among students who are most at risk of disengaging from science learning and who are traditionally underrepresented in science, technology, engineering, and mathematics fields (STEM; Morgan et al., 2016; Quinn & Cooc, 2015). Additionally, recent research suggests the need to account for a general overarching engagement factor together with specific dimensions of engagement (Morin & Marsh, 2015; Wang et al., 2016). Modeling both general and specific dimensions of engagement align with the theoretical view that student engagement is a multidimensional construct, encompassing both general engagement in learning tasks, as well as specific manifestations of that engagement (Wang et al., 2016). In other words, the global engagement factor represents the conceptually related aspects of the specific behavioral, affective, and cognitive engagement dimensions.

This study aims to address these gaps in the literature by identifying unique profiles that represent how a global and distinct engagement dimensions combine within a sample of diverse middle school students in science. Based on recent work examining the multidimensionality of engagement (Ben-Eliyahu, Moore, Dorph, & Schunn, 2018; Wang et al., 2016) we first tested and applied a bifactor exploratory structural equation model (ESEM) that specified a global engagement factor in addition to the three engagement dimensions. Second, we applied the bifactor ESEM in the latent profile analysis (LPA) to identify unique engagement profiles in science. Third, we explored how key motivation predictors, including achievement goal orientations and self-efficacy, predict profile membership. Finally, we examined the relationships among engagement profiles and science achievement.

2. Engagement profiles identified in past studies

Findings from a small number of engagement profile studies indicate that students experience various dimensions of engagement simultaneously and that these engagement dimensions co-occur within students in unique ways. Further, these studies show that different engagement profiles can have either beneficial or undesirable relationships to student outcomes (see Appendix A for summary). For example, Wang and Peck (2013) examined patterns of school engagement profiles among high school (grades 9 to 11) students (57% African American, 43% European American). Based on a LPA using three continuous indicators of behavioral, cognitive, and affective engagement, results showed that a five-profile solution best fit the data including Moderately Engaged, Engaged, Minimally Engaged, Emotionally Disengaged, and Cognitively Disengaged profiles. As expected, the Engaged profile was predictive of higher GPA, educational aspiration, low dropout rates, higher college enrollment rates, and low depression rates, and the opposite trend was found among the Minimally Engaged group (Wang & Peck, 2013). In a more recent study, Salmela-Aro, Moeller, Schneider, Spicer, and Lavonen (2016) examined profiles of engagement-burnout symptoms among high school students from both the United States and Finland (grades 9 to 12) and identified a similar set of four profiles: Engaged, Engaged-Exhausted, Moderately Burned Out, and Burned Out. These profiles indicated that among certain subgroups of students in both Finland and the U.S., there is a 'dark' side of engagement; that is, students who simultaneously experience high levels of engagement and burnout (Salmela-Aro et al., 2016). Additionally, the profiles differed in their experiences of situational demands, resources, and engagement in school (Salmela-Aro et al., 2016). Finally, van Rooij et al. (2017) identified five engagement profiles among 12th grade students in Germany, which included two indices of engagement (behavioral, cognitive), as well as need for cognition (or 'intellectual engagement'), and self-efficacy. The five profiles identified included: Intellectually highly disengaged, Behaviorally and cognitive disengaged, Overall average engaged, Intellectually engaged, and Overall highly engaged. Their results showed that the Engaged group scored higher on various measures of academic adjustment (e.g., motivation) and achievement (e.g., GPA) after transitioning to a university, whereas the opposite trend was observed for the students in the profiles characterized by low behavioral and cognitive engagement, as well as intellectual disengagement (van Rooij et al., 2017).

Findings across these studies provide converging evidence that profiles characterized by higher engagement are more positively related to desirable academic outcomes, whereas the reverse is true for profiles characterized by low engagement. Conversely, findings regarding the nature of engagement profiles characterized by moderate or differentiated configurations of engagement indices are mixed. For example, while both Wang and Peck (2013) and van Rooij et al. (2017) identified moderately engaged profiles (average ratings on all engagement indicators), Wang and Peck (2013) also identified an emotionally disengaged (low affective engagement, but moderate to high cognitive and behavioral engagement), and a cognitively disengaged (low cognitive engagement, but moderate to high affective and behavioral engagement) profile. In contrast, van Rooij et al. (2017) identified a profile characterized by *both* low behavioral and low cognitive engagement.

Comparisons across engagement profile studies must be made cautiously however, as there are important theoretical and methodological differences that influence the class solutions identified. First, the majority of existing studies included indicators representing constructs outside of engagement, such as burnout (e.g., Salmela-Aro et al., 2016; Tuominen-Soini & Salmela-Aro, 2014) or need for cognition and academic interest (e.g., van Rooij et al., 2017). Second, the measures of behavioral, affective, and/or cognitive engagement, when included, differed across studies (e.g., van Rooij et al., 2017; Wang & Peck, 2013). Third, most of the existing engagement profile studies examined either some or none of the traditional markers of engagement from Fredricks et al.'s (2004); Fredricks, Wang, et al.'s (2016) framework; one study included only cognitive and behavioral engagement (van Rooij et al., 2017), and other studies used a composite score of school engagement to determine profiles (e.g., Salmela-Aro et al., 2016; Tuominen-Soini & Salmela-Aro, 2014). Thus, engagement profiles identified in past studies are not based on a common set of indicators, measures, and/or theoretical framework.

This study examines engagement profiles based on the three dimensions that correspond to Fredricks et al.'s (2004); Fredricks, Wang, et al.'s (2016) framework of engagement in school. Despite the large body of variable-centered literature that demonstrates the importance of behavioral, cognitive, and affective engagement for students' learning, to our knowledge, there is only one person-centered study to date that has used all three dimensions to identify student engagement profiles (Wang & Peck, 2013). We also applied a bifactor ESEM to account for a global engagement factor that captures the commonality shared by the specific dimensions, and allow us to examine the unique contributions of specific dimension over and above the global factor (Ben-Eliyahu et al., 2018; Rodriguez, Reise, & Haviland, 2016; Wang et al., 2016). For example, Wang et al. (2016) showed that the specific engagement dimensions predicted science achievement and intentions to pursue STEM college majors independent of the global factor (Wang et al., 2016). Not accounting for a global factor may obscure the multidimensionality of engagement, and in turn, mask possible differences between the specific engagement dimensions (DeMars, 2013; Wang et al., 2016). This approach to specifying construct multidimensionality also provides less biased estimates in person-centered analyses by estimating the variance common to a group of items (specific factors) beyond the scale as a whole (general factor; Asparouhov, Muthén, & Morin, 2015; Reise, Bonifay, & Haviland, 2013).

3. Antecedents and outcomes of science engagement profile membership

Whereas engagement is conceptualized as the ways in which students actively connect to learning in the classroom, motivation refers to the psychological or physiological drive that precedes students' learning behaviors (e.g., Anderman & Maehr, 1994; Midgley et al., 2001; Patall, Vasquez, Steingut, Trimble, & Pituch, 2016). We drew on achievement goal orientation theory, a motivation framework used to better understand why students engage in learning and strive to achieve in academic contexts (see Hulleman, Schrager, Bodman, & Harackiewicz, 2010; Senko, Hulleman, & Harackiewicz, 2011; Wormington & Linnenbrink-Garcia, 2017 for reviews). The three goal orientations include mastery (focused on developing proficiency), performance-approach (focused on demonstrating competence), and performance-avoidance (focused on avoiding the appearance of incompetence) orientation (Harackiewicz, Barron, Tauer, & Elliot, 2002; Midgley & Urdan, 2001; Pintrich, 2000). A positive relationship between mastery orientation and engagement in science is well-established (e.g., Lee et al., 2016; Ben-Eliyahu et al., 2018; Pugh et al., 2010; Schnell, Ringeisen, Raufelder, & Rohrmann, 2015; Singh et al., 2002). In contrast, studies indicate that performance-oriented goals (particularly performance-avoidance goals) are commonly linked to lower engagement in school (Hulleman et al., 2010; Lau & Nie, 2008; Lau & Roeser, 2008; Midgley et al., 2001). For example, learning environments that promote social comparisons and competition (aligned with performance-oriented goals) have been linked to undermining deep cognitive engagement (Wigfield et al., 2006). Similarly, students who experience high levels of externally imposed goals can feel behaviorally and emotionally disengaged from school over time (Pajares, Britner, & Valiante, 2000). Of note however, the research related to performance-approach goals and achievement is less clear, with some studies showing that the latter is sometimes associated with greater motivation and learning, particularly when coupled with mastery goals (e.g., Harackiewicz et al., 2002; Linnenbrink, 2005).

We also examined self-efficacy, or the beliefs that students have in their academic abilities and the outcomes of their efforts (Bandura, 1997; Pajares, 1996; Usher & Pajares, 2008) as an antecedent of science engagement. The literature demonstrates self-efficacy as a key factor in students' engagement, perseverance, and achievement in science (Lee et al., 2016; Britner & Pajares, 2006; Chen & Pajares, 2010). A recent study showed that fifth and sixth grade students' self-efficacy consistently predicted various dimensions of affective, cognitive, and/or behavioral engagement in both formal and informal science learning environment (Ben-Eliyahu et al., 2018). Studies have also shown that self-efficacy and mastery goals work together in productive ways to support science engagement and learning (Lee et al., 2016; Bae & DeBusk-Lane, 2018; Pajares, 1996; Pajares et al., 2000).

Finally, because demographic characteristics are known to be at least weakly associated with students' motivation and engagement in science, gender, grade level (6, 7, or 8), and minority status were included as controls. In terms of gender, there is a tendency for girls to report higher levels of engagement compared to boys (Marks, 2000; Meece, Glienke, & Burg, 2006; Sirin & Rogers-Sirin, 2005). We also accounted for grade level, as studies show that students' engagement in school can change considerably from year to year in (e.g., Bae amp; DeBusk-Lane, 2018; Caprara et al., 2008; Guo, Marsh, Parker, Morin, & Dicke, 2017; Shim, Ryan, & Anderson, 2008). Finally, minority status was accounted for, as past studies have shown gaps in science achievement along racial and ethnic lines (Johnson, Crosnoe, & Elder Jr, 2001; Morgan et al., 2016; Perez et al., 2019).

Furthermore, we examined the relationship between engagement profiles and science achievement, which aids in substantive profile interpretability (Morin, Meyer, Creusier, & Biétry, 2016). Recent person-centered studies of engagement show that students' engagement profiles are linked to multiple academic outcomes, including GPA, successful transition to university, and academic adjustment (e.g., Tuominen-Soini & Salmela-Aro, 2014; van Rooij et al., 2017; Wang & Peck, 2013). Whereas profiles characterized by higher engagement in school are consistently associated with more positive academic outcomes and the reverse is found for profiles characterized by disengagement, the relationships between profiles characterized by moderate or varying levels of engagement and academic outcomes are mixed (e.g., van Rooij et al., 2017; Wang & Peck, 2013). For example, whereas the moderately engaged profile in van Rooij et al.'s (2017) study was associated with positive academic outcomes (e.g., higher GPA), in Wang and Peck's (2013) study, the moderately engaged profile was associated with lower GPA and moderate levels of depression. Thus, this study aims to clarify the mixed findings related to how engagement profiles relate to learning outcomes. Further, compared to the global educational outcomes examined in previous person-centered studies (e.g., GPA, enrollment rates), we examined more proximal learning outcomes in science, which included students' knowledge of key concepts in earth, life, and physical sciences that correspond to their grade-specific science curriculum.

4. Present study

In the present study, we aimed to identify engagement profiles among middle school students in science. We also assessed how students' achievement goal orientations and self-efficacy predicted the likelihood of profile membership, accounting for demographic characteristics (gender, grade, and minority status). Finally, we examined the relationship between the engagement profiles and science achievement. The following research questions guided this study:

(1) Which student profiles emerge in middle school science from the specific (behavioral, cognitive, affective) and global dimensions of engagement?
(2) Do students' motivation (achievement goal orientation, self-efficacy) predict profile membership, after accounting for demographic characteristics?
(3) Do the engagement profiles differentially relate to science achievement?

Based on existing engagement profile studies, we expected to identify between four to five profiles, including a profile characterized by high or moderately high engagement across all four indicators and low or moderately low engagement across all four indicators (e.g., Salmela-Aro et al., 2016; van Rooij et al., 2017; Wang & Peck, 2013). We also expected to identify additional profiles characterized by low engagement on one of the specific dimensions (e.g., behaviorally disengaged, van Rooij et al., 2017; cognitively disengaged, emotionally disengaged, Wang & Peck, 2013). Although the configuration of engagement profiles that demonstrate shape effects differ from study to study, because the engagement indicators used here most resemble those of the Wang and Peck (2013) study, we expected to also identify a cognitively disengaged and an emotionally disengaged profile. However, given the small number of engagement profile studies, the identification of these additional profiles were largely exploratory.

We also expected that mastery orientation and self-efficacy would predict membership in more highly engaged profiles, and that performance goals would predict membership in less engaged profiles. These expectations were based on literature that shows that mastery goals work in service of deep engagement focused on understanding and developing skills, whereas performance goals are associated with adverse learning behaviors such as withdrawal, disengagement, and maladaptive coping (e.g., Lau & Nie, 2008; Lau & Roeser, 2008; Pajares et al., 2000). Specifically, we expected performance-avoidance goals to be most predictive of membership in less engaged profiles, as the literature on performance-approach goals is mixed (e.g., Bae & DeBusk-Lane, 2018; Harackiewicz et al., 2002; Linnenbrink, 2005; Pintrich, 2000). Finally, we expected profiles characterized by high levels of engagement to be associated with higher science achievement, and the profiles characterized by lower levels of engagement to be associated with lower science achievement (e.g., Wang & Peck, 2013). The expected relationships between engagement profiles characterized by different configurations of engagement dimensions and outcomes were exploratory, given the mixed findings in the literature.

5. Method

5.1. Sample and procedures

A total of 1125 students in grades 6 ($n = 351$), 7 ($n = 400$), and 8 ($n = 362$) from 26 schools across seven urban school districts in the western region of the United States participated in the study (12 students did not report grade level). Students of teachers participating in a larger science education project were recruited to participate in this study. Teachers, students, and parents were informed that the purpose of the study was to better understand approaches to support students' engagement and achievement in science. The student sample included male (45.76%) and female (54.24%) students, between 11 and 13 years of age, who identified as American Indian (0.18%), Asian/Pacific Islander (19.95%), African American/Black (6.83%), Hispanic or Latinx (45.28%), Caucasian/White (26.06%), or Two or more Races (1.70%). Students' ethnic minority status (all ethnicities except for White and Asian/Pacific Islander) was coded 1 = yes and 0 = no (e.g., Chen, 2012). This decision was made because compared to White and Asian students, Native American, African American, and Hispanic/Latinx students are typically underrepresented in science (National Science Foundation & National Center for Science and Engineering Statistics, 2017; Morgan et al., 2016). Students attended schools where 52.8% of the students qualified for Free and Reduced Lunch (FRL) and 17.6% were identified as English Language Learners. Approval from the university's institutional review board was obtained, and parental permission was granted on a signed consent form prior to data collection. Self-report questionnaires and concept inventories (CIs) were administered via paper-and-pencil by the teacher. Students completed the measures during regularly scheduled class time and were informed that their participation was voluntary.

5.2. Measures

The engagement, achievement goal orientation, and self-efficacy items were rated on a 5-point Likert like scale (1 = *Not true at all*, 2 = *Not true*, 3 = *Somewhat true*, 4 = *True*, 5 = *Very true*). For the three engagement dimensions (behavioral, affective, and cognitive), three achievement goal orientations (mastery, performance-approach, performance-avoidance), and self-efficacy, factor subscale scores were computed. Evidence for the reliability (internal consistency, test-retest, factor structure) and validity (construct, external) of the questionnaires ratings and CI scores for use in middle school science classrooms is reported in a prior study (Lee et al., 2016).

5.2.1. Science engagement

The three types of science engagement, including behavioral (3 items, $\alpha = 0.74$, e.g., "I follow the rules in my science class"), affective (3 items, $\alpha = 0.76$, e.g., "I feel excited about the learning activities in my science class", and cognitive (3 items, $\alpha = 0.73$, e.g., "During science class, I ask questions and offer suggestion") engagement was assessed using a science engagement scale adopted from Fredricks, Wang, et al. (2016).

5.2.2. Achievement goal orientation

Three achievement goal orientation scales, including mastery (3 items, $\alpha = 0.67$, e.g., "One of my goals in science class is to learn as much as I can"), performance-approach (3 items, $\alpha = 0.83$, e.g., "One of my goals is to show others that science class work is easy for me."), and performance-avoidance (3 items, $\alpha = 0.75$, e.g., "It's important to me that my science teacher doesn't think that I know less than others in class.") goals was used. The items were adapted from the Patterns of Adaptive Learning Survey (PALS; Midgley et al., 2000) to ask students about their goal orientations in the context of their science classroom.

5.2.3. Science self-efficacy

Science self-efficacy was assessed using 3 items ($\alpha = 0.79$) that asked students about their self-efficacy in science (e.g., "Even if the science classwork is hard, I can do it"). The items were adapted from PALS (Midgley et al., 2000) to ask students about their science self-efficacy.

5.2.4. Science achievement

Science achievement was measured using multiple-choice science CI that corresponded to students' grade level content. The earth science CI (grade 6) consists of 30 items from a validated assessment tool (Libarkin, Kurdziel, & Anderson, 2007) ($\alpha = 0.86$). The life science CI (grade 7) consists of 18 items that were adapted from the Conceptual Inventory of Natural Selection (Anderson, Fisher, & Norman, 2002) ($\alpha = 0.84$). The physical science CI (grade 8) consists of 25 items ($\alpha = 0.71$) developed and validated by the Physics Underpinnings Action Research Team from Arizona State University (Evans et al., 2003). Science CI scores represent the total standardized percentage correct.

5.3. Analyses

5.3.1. Measurement models

We used Mplus 8 (Muthén & Muthén, 1998–2017) with maximum likelihood estimation with robust standard errors (MLR). Prior to conducting the LPA, preliminary analyses were conducted to assess the multidimensional factor structure of engagement, which included a CFA, bifactor CFA, ESEM, and bifactor ESEM. First, a CFA was tested, with each of the three latent dimensions specified by the three conceptually corresponding items and all cross-loadings set to zero. Next, a bifactor CFA model was tested, in which all items were allowed to load on the global factor, and on its conceptually aligned dimension of engagement, while still restricting cross-loadings to zero. Overall model fit was assessed using the cut-off criteria recommended by Hu and Bentler (1998, 1999) including the Comparative Fit Index (CFI ≥ 0.90), the Tucker-Lewis Index (TLI ≥ 0.90), the root mean square error of approximation (RMSEA ≤ 0.06), and the standardized root mean square residual (SRMR ≤ 0.06). Next, we tested an ESEM model, in which all 9 engagement items were specified to load on each of the three engagement factors, while allowing for non a-priori item-factor relations to be 'targeted' to be as close to zero and freely estimated through target rotation (Asparouhov & Muthen, 2009). The inspection of bifactor and ESEM models allowed for a direct test of construct-relevant multidimensionality; that is, whether the items relate to more than one source of true-score variance due to conceptually related constructs (Morin et al., 2017).

To compare the ESEM against the CFA measurement model, factor correlations were examined (Morin et al., 2017). Because an ESEM approach provides more precise estimates of factor correlations when cross-loadings are present in the population (Asparouhov et al., 2015), results would favor the ESEM over the CFA model if distinct patterns of factor correlations are observed. Using a similar approach, a bifactor ESEM was tested, which specifies a global latent factor of engagement underlying the ratings to items designed to measure the three specific dimensions of engagement. All engagement items were freely estimated for the global engagement factor, while the three specific engagement factors specified as described in the ESEM framework using orthogonal target rotation (Reise, 2012). To compare the bifactor ESEM to the ESEM, the factor loadings between the two models were compared for theoretical alignment (Morin et al., 2017). Moderate factor loadings for all engagement items on the global engagement factor, and higher factor loadings for items that correspond to the specific engagement factors, would provide evidence for the fit of the bifactor ESEM. For both the ESEM and bifactor ESEM models, the criteria used for the CFA was used to assess model fit.

5.3.2. Latent profile analysis (LPA) of middle school engagement

The LPAs were estimated using 1000 random starts, 250 final stage optimizations, and 50 initial stage iterations. To avoid local maximum, the final model was estimated with 6000 random starting values, 1000 iterations, and 200 final stage optimizations (Hipp & Bauer, 2006; Masyn, 2013). The 'mixture complex' Mplus option was used to account for grouping effect stratification (students nested in classrooms). This takes into account the non-independence in observations when computing the standard errors. During enumeration, all profile means were freely estimated and item variances constrained equal between profiles, as this is a default in Mplus and supports substantive interpretation of the profiles (Masyn, 2013). Factor scores from the bifactor ESEM were used as indicator items in the LPA analyses because factor scores control for measurement error by giving more weight to items that exhibit less measurement error (Morin & Marsh, 2015).

Models were selected based on multiple statistical indices, theoretical interpretability, and substantive meaningfulness (Marsh, Lüdtke, Trautwein, & Morin, 2009; Nylund, Asparouhov, & Muthén, 2007). Statistical indices included minimum values of Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and sample-size adjusted BIC (aBIC). Smaller values of AIC, BIC, and aBIC estimates indicate more parsimony when comparing models (Collins & Lanza, 2013; Geiser, 2013). The entropy value and classification probabilities were also examined, with values closer to 1 indicating higher precision and reliability of classification (Jung & Wickrama, 2008; Lubke & Muthén, 2007). We also assessed the bootstrapped likelihood ratio test (BLRT), and the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT) to compare models (Muthén & Asparouhov, 2012). These model comparison tests compare the model with k latent classes to the model with k-1 latent classes, whereby a non-significant p-value indicates the k-1 class should be favored (Muthén & Asparouhov, 2012). Of note, the class enumeration procedure can be heavily influenced by large sample sizes, in which the indices (e.g., AIC, aBIC, and BLRT) continue improving with the addition of latent profiles making the selection of the optimal number of latent profiles unclear (Marsh et al., 2009). We therefore also graphically represented the information criteria using 'elbow plots' to illustrate the changes in fit associated with additional profiles (Morin, Morizot, Boudrias, & Madore, 2011; Petras & Masyn, 2010). In these plots, the point after which the slope plateaus indicates the optimal number of latent profiles into which the cases are classified.

5.3.3. Predictors and outcomes of profile membership

Predictors (gender, minority status, grade, achievement goal orientations, and self-efficacy) and outcome (science achievement) were examined in relation to the engagement profiles (Morin & Litalien, 2017). Each predictor was included in a series of multinomial logistic regressions to examine how each predictor, accounting for the others, influenced the likelihood of membership in the engagement profiles. Specifically, k-1 regression coefficients were generated in relation to a reference profile in the form of log odds (Muthén & Muthén, 1998–2017). To aid in interpretation, each log odds was transformed into odds ratios that present the likelihood of profile membership. To assess science achievement across the profiles, we used the Mplus BCH function that estimates the equality of means between profiles with Wald chi-square analyses (Asparouhov & Muthén, 2014).

6. Results

6.1. Multidimensional factor structure of engagement

Descriptive and reliability statistics for all observed variables are presented in Table S1 of the online supplement materials. Both the CFA and the bifactor CFA measurement models showed adequate fit to the data, with the bifactor CFA model demonstrating a slight improvement in fit. Similarly, the bifactor ESEM showed improved fit over the ESEM (Table 1). Thus, based strictly on the fit statistics, results suggest that the bifactor ESEM should be retained (Morin et al., 2017). In addition to the fit statistics, the parameter estimates (factor loadings and correlations) of the measurement models were examined for theoretical conformity. The CFA and ESEM solutions were compared to investigate whether construct-relevant multidimensionality was present (Table S2). The three a priori dimensions of engagement appeared to be well-defined, as represented by high factor loadings in both the CFA ($\lambda = 0.58$ to 0.82), and the ESEM ($\lambda = 0.54$ to 0.80).

When comparing the factor correlations, results showed that the estimated factor correlations are lower in the ESEM ($r = 0.50$ to 0.63) compared to the CFA ($r = 0.53$ to 0.66), indicating that the factors are more clearly differentiated in the ESEM. Additionally, the factor correlations remained moderate in the ESEM, suggesting that a global engagement factor may better represent that data. When comparing the bifactor ESEM to the ESEM, the bifactor ESEM demonstrated superior model fit (Table 2). The global engagement factor was defined by strong and positive factor loadings for all engagement items ($\lambda = 0.35$ to 0.74). Additionally, in the bifactor ESEM, all three specific engagement factors retained specificity; that is, the items defining behavioral ($\lambda = 0.37$ to 0.66), cognitive ($\lambda = 0.49$ to 0.52), and affective ($\lambda = 0.34$ to 0.50) engagement loaded clearly on their corresponding factors. Taken together, the bifactor ESEM showed evidence for the multidimensionality of engagement, as well as the presence of a global engagement factor. The four factor scores (global and three dimensions) were therefore retained and used to identify engagement profiles (Morin et al., 2017).

6.2. Science engagement profile solution

The fit indices for 2 to 7 latent profiles solutions are presented in Table 3. As is common with large sample sizes, the information criterion values continued improving with the addition of latent profiles, providing limited information to determine the optimal class solution.

Table 1
Goodness-of-Fit Statistics from the alternative measurement models.

CFA model	χ^2	*df*	*p*-Value	RMSEA	CFI	TLI	SRMR
CFA	40.547	24	0.019	0.025	0.992	0.989	0.020
Bifactor CFA	30.921	18	0.029	0.025	0.994	0.988	0.017
ESEM	18.060	12	0.114	0.021	0.997	0.992	0.011
Bifactor ESEM	5.588	6	0.471	0.000	1.00	1.00	0.004

Table 2
Standardized factor loadings (λ) for the bifactor ESEM solution.

Item	Behavioral (λ)	Affective (λ)	Cognitive (λ)	Global engagement λ
Behavioral 1	**0.38**	0.049	0.07	0.58***
Behavioral 2	**0.66***	0.088	0.08	0.37
Behavioral 3	**0.37**	−0.17	−0.23	0.74
Affective 1	0.001	**0.50**	0.09	0.65*
Affective 2	−0.006	**0.42**	0.01	0.65*
Affective 3	0.05	**0.34***	0.06	0.45**
Cognitive 1	−0.05	0.04	**0.49**	0.56
Cognitive 2	−0.03	0.02	**0.50**	0.52
Cognitive 3	0.07	0.08	**0.52*****	0.35**

Note. Bold coefficients reflect target factor loadings on the specific factors.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Therefore, we relied on other indicators, including a small decrease in BIC values (Nylund et al., 2007) and profiles that were substantively distinguishable based on theory and prior research (Marsh et al., 2009). We also examined elbow plots of the information criteria (Morin et al., 2011; Petras & Masyn, 2010). The elbow plots indicated that improvements in the information criteria reached a plateau around five classes (Fig. S1).

Further, the addition of a sixth profile resulted in an arbitrary division of the profile characterized by moderate engagement across the four dimensions, whereas a five profile solution resulted in a qualitatively distinct and theoretically meaningful profiles that have been identified in past studies (van Rooij et al., 2017; Wang & Peck, 2013). The five-profile solution that was retained (Fig. 1) showed adequate classification accuracy (entropy = 0.73). The profile labels were based on the most prominent engagement dimension that fell one or more *SD* above or below the mean. If all of the dimensions were clustered around the mean (i.e., approximately 0.5 or less *SD* above or below the mean), this pattern was depicted in the label using the term 'moderately'. Finally, it is important to note that when interpreting the profiles, the indicators for the three specific dimensions of engagement represent the residual variability over-and-above the global factor (Chen, West, & Sousa, 2006; DeMars, 2013). In other words, the global factor captures the shared variance, or conceptual relatedness of the specific behavioral, affective, and cognitive factors, and the specific dimensions represent the unique variability across profiles after accounting for the shared variance represented by the global factor.

The five-profile solution included two profiles characterized by students with either moderately high or moderately low science engagement across all four indicators. These profiles were labeled *Moderately Engaged* (global, behavioral, affective, and cognitive engagement approx. 0.25 *SD* above the mean), and *Moderately Disengaged* (global, behavioral, affective, and cognitive engagement close to the mean or approx. 0.25 to 0.50 *SD* below the mean), respectively. The next three profiles represented qualitative differences across the four engagement indicators. These profiles were labeled *Disengaged* (global engagement approx. 2.5 *SD* below the mean), *Behaviorally Engaged* (behavioral engagement approx. 1 *SD* above the mean), and *Behaviorally Disengaged* (behavioral engagement approx. 1 *SD* below the mean). Notably, the *Disengaged* profile was also characterized by low behavioral engagement (approx. 1 *SD* below the mean) and moderate cognitive and affective engagement (approx. 1 and 0.25 *SD* above the mean, respectively), whereas for the *Behaviorally Engaged* and *Behaviorally Disengaged* profiles, the other three engagement indices fell approx. 0.5 to 1 *SD* below the mean. Therefore, accounting for a strongly negative global engagement, students exhibited systematically different responses for the specific engagement factors.

The *Moderately Engaged* profile had the highest number of students (55.95%, $n = 629$), followed by the *Moderately Disengaged* profile (17.85%, $n = 201$) and the *Behaviorally Disengaged* profile (16.0%, $n = 180$). The *Behaviorally Engaged* profile had the second lowest number of students (8.62%, $n = 97$) and the *Disengaged* profile (1.6%, $n = 18$) represented the smallest profile. Of note, although the *Disengaged* profile was small in size, this profile was also present in the 4-profile and 6-profile solutions, was identified in prior engagement profiles studies (e.g., van Rooij et al., 2017; Wang & Peck, 2013), and was theoretically meaningful (e.g., Fredricks, Wang, et al., 2016). Thus, we selected to retain the *Disengaged* profile because these students provided unique indicator variable responses that have substantive explanatory value.

6.3. Predictors of science engagement profiles

Predictors (grade, gender, minority status, goal orientations, self-efficacy) were added to the LPA model. The multinomial logistic regression log odds are reported in Table 4. Gender and minority status were not statistically significant predictors of profile membership. Grade level showed to be a significant predictor of profile membership in two cases; students in higher grades were approximately 60 to 70% more likely to be in the *Moderately Engaged* relative to the *Behaviorally Engaged* profile, and more likely to be in the *Moderately Disengaged* profile relative to the *Behaviorally Engaged* profile.

There were significant associations between mastery orientation, self-efficacy, and the likelihood of membership in the various engagement profiles. As expected, results showed that mastery orientation and self-efficacy predicted membership into a higher engagement profile relative to a lower engagement profile. Notably, for every one unit increase in mastery-orientation and self-efficacy, students were approximately seven times more likely to be in the *Moderately Engaged* profile relative to the *Moderately Disengaged* profile; and approximately two to four times more likely to be in the *Moderately Engaged* profile relative to the *Behaviorally Disengaged* profile. Similarly, mastery-orientation and self-efficacy showed to be significant predictors of lower likelihood of membership in less engaged profiles; for example, for every one unit increase in mastery orientation or self-efficacy, students were approximately 70% less likely to be in the *Moderately Disengaged* profile relative to the *Behaviorally Engaged* profile, 85% less likely to be in the

Table 3
Latent profile analysis fit statistics for 2 to 7 class solutions.

$N_{Classes}$	Log L.	AIC	Δ AIC	BIC	Δ BIC	VLMR-LRT	*p* value	Entropy
2	−5208.74	10,443.48	–	10,508.82	–	135.82	< 0.001	0.62
3	−5150.93	10,337.87	−105.61	10,428.34	−80.48	115.61	0.30	0.71
4	−5097.82	10,241.64	−96.23	10,357.25	−71.09	106.22	0.02	0.70
5	**−5051.20**	**10,158.39**	**−83.25**	**10,299.13**	**−58.12**	**93.25**	**0.09**	**0.73**
6	−5018.20	10,102.40	−55.99	10,268.27	−30.86	65.99	0.04	0.77
7	−5000.40	10,076.80	−25.60	10,267.81	−0.46	35.60	0.05	0.79

Note. LogL = Log Likelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; aBIC = sample size adjusted Bayesian Information Criterion; VLMR-LRT = Vuong Lo-Mendell-Rubin Likelihood Ratio Test. Minimal BIC indicates best relative fit. Significant VLMR denotes an improvement in fit given the additional class. Bold values represent the final model selected.

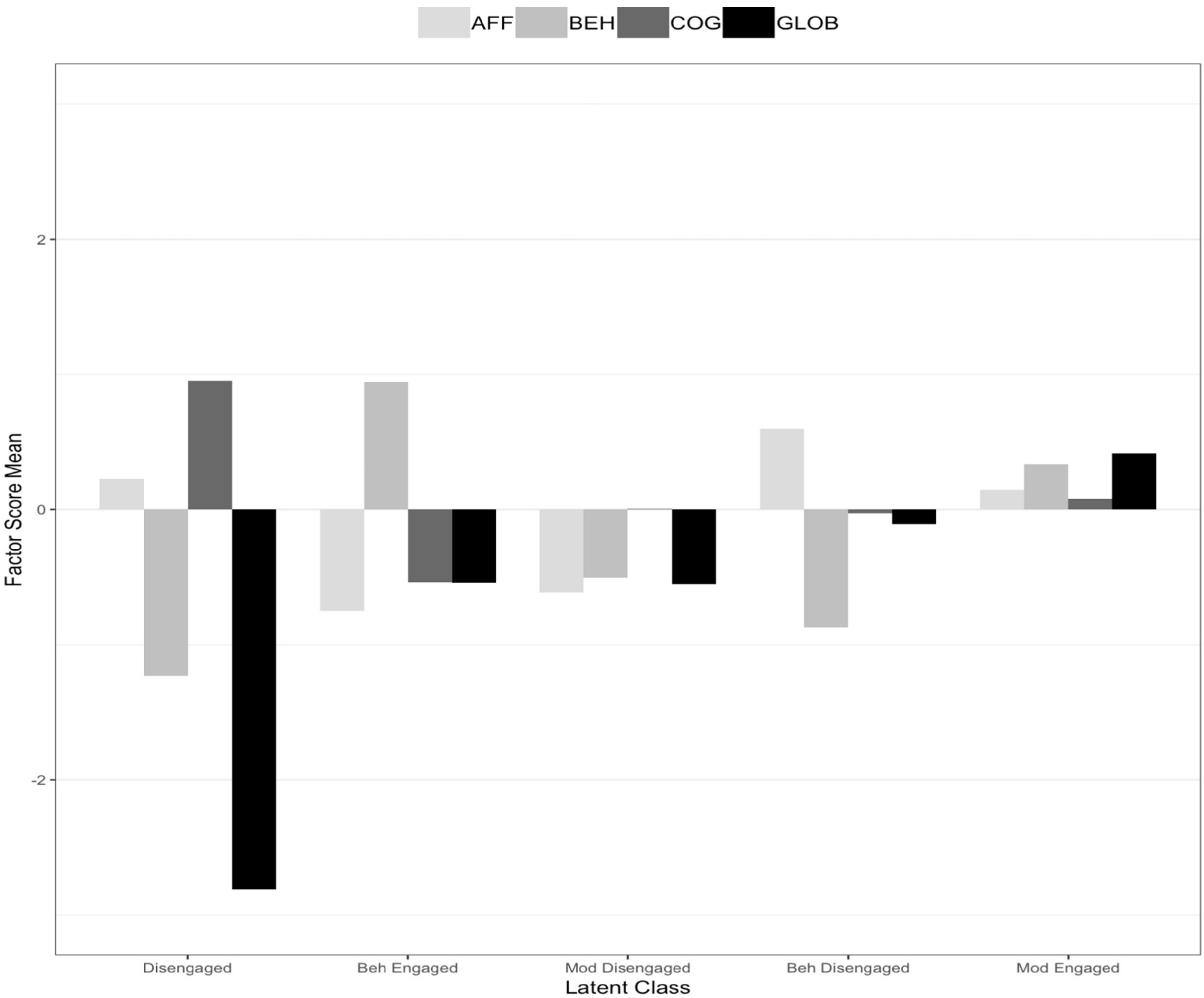

Fig. 1. Z-standardized mean scores of students' affective (AFF), behavioral (BEH), cognitive (COG), and global (GLOB) engagement indicators for the 5-profile solution.

Table 4
Multinomial logistic regressions of the predictors on profile membership.

Predictor	Profile 1 vs. 5			Profile 2 vs. 5			Profile 3 vs. 5			Profile 4 vs. 5			Profile 1 vs. 4		
	Coef.	SE	OR	Coef.	SE	OR	Coef.	SE	OR	Coef.	SE	OR	Coef.	SE	OR
Gender	0.17	0.75	1.18	0.18	0.25	1.19	0.17	0.33	1.19	0.20	0.32	1.22	−0.03	0.76	0.97
Minority	2.13	2.20	8.40	−0.39	0.28	0.68	0.29	0.42	1.34	−0.44	0.37	0.64	2.57	2.16	13.11
Grade	0.60	0.54	1.82	0.24	0.15	1.28	0.33	0.23	1.40	−0.21	0.23	0.81	0.81	0.54	2.25
Mastery	−1.29	0.77	0.27	**1.42****	0.29	4.12	−0.56	0.34	0.57	0.64	0.34	1.90	**−1.94****	0.74	0.14
Perf app	−0.06	0.66	0.94	0.02	0.19	1.02	−0.08	0.24	0.93	−0.01	0.25	0.99	−0.05	0.66	0.95
Perf avoid	−0.58	0.52	0.56	0.40	0.17	1.49	0.31	0.20	1.36	0.26	0.24	1.29	−0.84	0.53	0.43
Self-efficacy	**−2.18****	0.77	0.11	**0.76****	0.27	2.15	**−1.22****	0.39	0.30	**−0.88****	0.36	0.42	**−1.31***	0.67	0.27

	Profile 2 vs. 4			Profile 3 vs. 4			Profile 1 vs. 3			Profile 2 vs. 3			Profile 1 vs. 2		
	Coef.	SE	OR	Coef.	SE	OR	Coef.	SE	OR	Coef.	SE	OR	Coef.	SE	OR
Gender	−0.02	0.32	0.98	−0.03	0.34	0.97	0.00	0.71	1.00	0.004	0.31	1.00	−0.01	0.75	0.99
Minority	0.05	0.36	1.05	0.74	0.41	2.09	1.84	2.12	6.28	−0.68	0.38	0.51	2.52	2.17	12.42
Grade	**0.45***	0.23	1.58	**0.55***	0.25	1.73	0.27	0.51	1.31	−0.09	0.22	0.91	0.36	0.53	1.43
Mastery	**0.77***	0.36	2.17	**−1.20****	0.36	0.30	−0.74	0.65	0.48	**1.97****	0.34	7.20	**−2.71****	0.75	0.07
Perf App	0.03	0.26	1.03	−0.07	0.28	0.93	0.02	0.63	1.02	0.10	0.22	1.10	−0.08	0.65	0.92
Perf Avoid	0.15	0.26	1.16	0.05	0.24	1.05	−0.89	0.48	0.41	0.10	0.20	1.10	−0.99	0.52	0.37
Self-Efficacy	**1.64****	0.33	5.16	−0.34	0.26	0.71	−0.96	0.65	0.38	**1.98****	0.33	7.27	**−2.94****	0.71	0.05

Note. SE: standard error of the coefficient; OR: odds ratio; gender: 0 = male, 1 = female; minority: 0 = non-minority, 1 = minority; Grade: 6, 7, and 8; mastery = mastery approach; Perf App = performance approach; Perf Avoid = performance avoid. The coefficient/OR represent the effect of the predictor on the likelihood of membership into the first listed profile relative to the second listed profile. Profile 1: disengaged; profile 2: moderately engaged; profile 3: moderately disengaged; profile 4: behaviorally engaged; profile 5: behaviorally disengaged. Bold $^{*}p < 0.05$; $^{**}p < 0.01$.

Table 5
Associations between engagement profile membership and science achievement.

	Disengaged	Behavioral engaged	Moderately disengaged	Behavioral disengaged	Moderately engaged	Summary of significant differences
	M [CI]	*M* [CI]	*M* [CI]	*M* [CI]	*M* [CI]	
Gr 6 Sci Achiev	20.6 [13.5, 27.2]	34.8 [30.9, 38.8]	30.6 [25.9, 35.3]	31.9 [28.3, 35.5]	33.2 [31.3, 35.1]	1 < 2, 3, 4, 5
N	3	41	47	50	199	
Gr 7 Sci Achiev	33.0 [22.8, 43.1]	41.5 [36.7, 46.3]	30.3 [27.0, 33.6]	38.2 [34.8, 41.6]	37.8 [35.6, 40.0]	2 > 3, 3 < 4, 3 < 5
N	5	30	77	73	199	
Gr 8 Sci Achiev	29.0 [18.8, 39.0]	39.4 [31.3, 47.5]	31.4 [28.2, 34.6]	34.8 [29.6, 39.9]	41.6 [39.5, 43.8]	1 < 5, 3 < 5
N	6	24	66	42	199	

Note. All profile sizes were generated from the participants' modal class assignment; $n = 1061$. M = Mean; CI = 95% Confidence Interval, Gr6 Sci Achiev = Grade 6 Science Achievement, Gr7 Sci Achiev = Grade 7 Science Achievement, Gr8 Sci Achiev = Grade 8 Science Achievement.

Disengaged profile relative to the *Behaviorally Engaged* profile, and 95% less likely to be in the *Disengaged* profile relative to the *Moderately Engaged* profile. Performance-approach and -avoidance orientations were not statistically significant predictors of profile membership. Overall, results showed that grade was a significant but weak predictor of membership, whereas mastery orientation and self-efficacy were significant and strong predictors of membership in more highly engaged relative to less engaged profiles.

6.4. Outcomes of science engagement profiles

The within-profile means, 95% confidence intervals, and test of significance of each outcome are reported in Table 5. The associations between profiles and outcomes showed consistent patterns that generally aligned with our expectations. That is, the *Moderately Engaged* and *Behaviorally Engaged* profiles were associated with higher science achievement whereas the *Disengaged* and *Moderately Disengaged* profiles were associated with lower science achievement. The *Behaviorally Disengaged* profile was associated with science achievement that generally fell somewhere in between the lower and higher scores. Among the grade 6 students, the pairwise differences between the *Disengaged* profile, which was associated with the lowest science achievement, and all of the other four profiles were significant. In grade 7, the *Moderately Disengaged* profile was associated with the lowest science achievement, and this profile was significantly different from the *Moderately Engaged*, *Behaviorally Engaged*, and *Behaviorally Disengaged* profiles. Finally, in grade 8, significant pairwise differences were identified between the *Moderately Engaged* profile, which was associated with the highest science achievement, and the *Disengaged* and *Moderately Disengaged* profiles.

7. Discussion

This study contributes to our understanding of engagement profiles among a diverse sample of middle school students in science. We estimated the engagement profiles using a bifactor ESEM in the LPA, which accounts for a global factor in addition to the three specific engagement dimensions. Analyses revealed five engagement profiles that presented both normative and unique configurations across the four indicators of engagement. Significant motivation predictors of profile membership, including mastery orientation and self-efficacy, and significant relationships between engagement profiles and science achievement outcomes, were also identified.

7.1. Student engagement profiles in science

In relation to our first research question, we identified a *Moderately Engaged* profile characterized by moderately high levels of behavioral, affective, cognitive, and global engagement, and the counterpart of this profile, labeled *Moderately Disengaged*, characterized by moderately low engagement levels across all four indicators. The *Moderately Engaged* profile identified in this study closely resembles the *Moderately Engaged* profile (Wang & Peck, 2013) and the *Overall Average Engaged* profile (van Rooij et al., 2017) identified in past studies characterized by engagement indicators approximately 0.50 *SD* above the mean. Similarly, the *Moderately Disengaged* profile identified in this study closely resembles the *Minimally Engaged* (Wang & Peck, 2013) and *Behaviorally and Cognitively Disengaged* (van Rooij et al., 2017) profiles identified in past studies characterized by engagement indicators approximately 0.50 *SD* below the mean. Also similar to trends observed in past studies (e.g., Salmela-Aro et al., 2016; van Rooij et al., 2017; Wang & Peck, 2013), the profile characterized by moderate levels of engagement (i.e., *Moderately Engaged*) was the largest in size (55.95%), followed by the *Moderately Disengaged* profile (17.85%). Consistent with the self-system model of motivation (e.g., Sinatra et al., 2015; Skinner, Furrer, Marchand, & Kindermann, 2008) and prior person-centered work, our results demonstrate that at least for a large subgroup of students, engagement dimensions are closely connected, in similar ways.

Our identification of three profiles characterized by low engagement in science (i.e., *Disengaged, Moderately Disengaged,* and *Behaviorally Disengaged*) align with findings from past person- and variable-centered studies of engagement. That is, a juxtaposition between engagement and disengagement (or 'disaffection'; Patall et al., 2018; Skinner et al., 2008; van Rooij et al., 2017; Wang & Peck, 2013) has been suggested, with the latter characterized not merely as having lower levels of engagement, but rather, behaviors associated with boredom, absenteeism, frustration, passivity, and in more severe cases, truancy, anxiety, and delinquency (e.g., Fredricks, Wang, et al., 2016; Harris, 2011). Our results contribute to this literature by providing a more in-depth look into at least three different ways disengagement in science can manifest. These findings have implications for taking differentiated approaches to addressing the needs of students who lack engagement in science.

The *Disengaged* (1.6%) profile shared some characteristics of profiles identified in past studies (e.g., Minimally Engaged, Wang & Peck, 2013); however, was unique in that it represented students with more extreme levels of global and behavioral disengagement, but moderately positive cognitive engagement. The Disengaged profile seems to represent students who are generally disengaged and off-task, but may also demonstrate moderate intellectual connection to learning activities. In traditional academic contexts, this group of students are likely to have the most challenging time adjusting, as they are more likely to demonstrate detachment from science learning activities and exhibit undesirable (e.g., off-task) behaviors in the classroom that result in disciplinary action (Lau & Nie, 2008; Wang & Peck, 2013).

The *Behaviorally Disengaged* profile (16%; third largest in size) is qualitatively interesting in that it represented students with low behavioral engagement, but average levels of cognitive and global engagement, and moderately high levels of affective engagement. Students in this profile may generally exhibit off-task behaviors and/or more severe forms of behavioral disengagement (e.g., chronic absenteeism, delinquency), but may also demonstrate moderate emotional (affective) connection to learning activities. To support students in the *Disengaged* and *Behaviorally Disengaged* profiles, a dual approach of targeting behavioral disengagement, coupled with approaches that leverage students' cognitive or affective proclivities to science learning activities may be appropriate, whereas for students who are uniformly disengaged across all dimensions (i.e., *Moderately Disengaged*) a more comprehensive approach to targeting students' engagement in science may be needed.

Finally, we identified a *Behaviorally Engaged* profile (8.6%; second smallest in size) who reported high behavioral engagement, and moderately low levels of cognitive, affective, and global engagement. This profile can be characterized as the 'well-behaved' students who may however, otherwise be disengaged from the science learning activity. Past scholars have suggested that behavioral engagement in of itself is not sufficient for long-term academic success and well-being (Dotterer & Lowe, 2011; Skinner, Kinderman, & Furrer, 2009). That is, continued success also requires that students connect to science learning in meaningful cognitive (e.g., sense-making, sharing different ideas, modeling processes underlying complex phenomena) and affective (e.g., interest, toleration of ambiguity, excitement to tackle challenging tasks) ways (Azevedo, 2015; Christenson et al., 2012; Fredricks, Wang, et al., 2016). For students in the *Behaviorally Engaged* profile, an approach that targets their lack of cognitive and affective connection to science learning, while simultaneously leveraging behavioral engagement or on-task behaviors, may be most appropriate.

When looking across our engagement profiles, we see that the *Behaviorally Disengaged* and *Behaviorally Engaged* profiles are similar to engagement profiles identified in past studies that were also characterized by higher and/or lower engagement on one or two dimensions (e.g., *Behaviorally and Cognitively Disengaged,* van Rooij et al., 2017, *Emotionally Disengaged*, Wang & Peck, 2013). However, our findings are unique in that within these profiles, the behavioral dimension of engagement emerged as the most extreme indicator (approx. 1 *SD* above or below the mean). Another pattern identified among the *Disengaged*, *Behaviorally Engaged*, and *Behaviorally Disengaged* profiles was that cognitive and affective engagement tend to cluster in similar ways (both moderately high or low), whereas behavioral engagement would demonstrate a strong opposite tendency. This is differs from van Rooij et al. (2017) in which a behaviorally and cognitively disengaged profile was identified, as well as from the Wang and Peck (2013) study in which unique emotionally disengaged and cognitive disengaged profiles were identified. Taken together, our findings replicate some of the patterns presented in prior engagement profile studies, but additional research is needed to develop more clarity around the nature of profiles with unique or well-differentiated configurations of engagement indicators.

7.2. The role of motivation (achievement goal orientations, self-efficacy) in predicting students' engagement profile membership

In relation to the second research question, we examined the role of students' achievement goal orientations and self-efficacy in predicting science engagement profile membership, controlling for demographic characteristics. Results showed that mastery orientation and self-efficacy predicted that students are anywhere between two to seven times more likely to be in a more engaged profile relative to a more disengaged profile. These findings align with both variable-centered (e.g., Lee et al., 2016; Bae & DeBusk-Lane, 2018; Hulleman et al., 2010; Lau & Roeser, 2002) and person-centered (e.g., Lo, Chen, & Lin, 2017; Luo, Hogan, & Paris, 2011; Wormington & Linnenbrink-Garcia, 2017) studies that indicate that mastery orientation and self-efficacy positively influence students' subsequent engagement in learning, including their affective, cognitive, and achievement-related behaviors.

Based on our findings, we propose achievement goal theory and social-cognitive theory of self-efficacy as useful frameworks to target middle school students' science engagement. Past research has shown that promoting learning opportunities that provide students' with mastery as well as optimal vicarious, social, and physiological learning experiences promote self-efficacy beliefs and in turn, students' persistence, engagement, and achievement in science learning (Bandura, 1997; Britner & Pajares, 2006; Chen & Usher, 2013; Usher & Pajares, 2008). Teachers can support students' mastery-orientation and self-efficacy by creating learning opportunities that immerse students in autonomous, practice-based science activities such as sharing and testing scientific ideas, drawing from students' prior knowledge base and experiences, and developing explanations for phenomena in the natural world (Bae & DeBusk-Lane, 2018; Bae, DeBusk-Lane, Hayes, & Zhang, 2018; Baram-Tsabari & Osborne, 2015; Patall et al., 2016, 2018). This is especially critical for science learning in high-needs schools that serve students who are historically underrepresented in STEM, and where gaps in science learning opportunities and achievement continue to persist (Bae et al., 2018; Cothran & Ennis, 2000; Morgan et al., 2016; Quinn & Cooc, 2015).

On the other hand, we did not find that performance orientations predicted likelihood of membership in the less engaged profiles relative to higher engaged profiles. A possible reason for this is that the influence of performance goal pursuits on students' engagement is largely mixed. Specifically, although the literature generally shows that performance-avoidance orientation is maladaptive with respect students' engagement and achievement, findings regarding performance-approach orientation are somewhat inconclusive (e.g., Hulleman et al., 2010; Linnenbrink-Garcia, Tyson, & Patall, 2008). While some studies show that performance-approach orientation is also linked to maladaptive learning behaviors, others indicate that mastery- and performance-approach orientations can work together to support desirable learning behaviors and achievement (e.g., Conley, 2012; Lo et al., 2017). Further, scholars have empirically demonstrated that although conceptually distinct, performance-approach and -avoidance goals are strongly correlated and overlap in their relation to learning outcomes (Linnenbrink-Garcia et al., 2012; Midgley & Urdan, 2001). For example, some studies show that performance-approach and -avoidance goals are endorsed in similar ways, and are unrelated to science learning behaviors and outcomes (e.g., Lee et al., 2016; Linnenbrink, 2005). Our results corroborate the findings from these past studies, showing that performance goals were not statistically significant predictors of membership in the engagement profiles.

In summary, our findings align with prior work supporting the strong link between mastery goals, self-efficacy, and engagement in science. We also provide additional evidence that is in line with recent studies showing that the relationships between performance orientations and engagement may not necessarily be characterized by the reverse trend, but rather, be weak and not significant in nature (Lee et al., 2016; Bae & DeBusk-Lane, 2018). In line with recent science education reform (NGSS Lead States, 2013; NRC, 2012) and the literature on supporting adaptive forms of motivation and engagement in science learning (e.g., Lee et al., 2016; Bae & DeBusk-Lane, 2018; Bae et al., 2018; Greene et al., 2008; Pugh et al., 2010; Sinatra et al., 2015), findings from this study show that creating mastery-driven science learning opportunities that focus on deeply understanding content and building students' sense of confidence in their science learning ability is important for fostering engagement.

7.3. Outcomes of students' motivation profiles

To answer the third research question, the relationship between the five engagement profiles and science achievement were examined for each middle school grade. Results aligned with our expectations, showing that profiles characterized by higher engagement (*Moderately Engaged, Behaviorally Engaged*) were associated with higher science achievement compared to profiles characterized by lower engagement (*Moderately Disengaged, Disengaged*). This finding aligns with the well-established variable-centered literature showing that engagement is strongly related to a range of desirable STEM outcomes (e.g., Fredricks, Filsecker, & Lawson, 2016; Sinatra et al., 2015).

Our results also support recent person-centered studies showing that profiles characterized by a combination of low behavioral, affective, and cognitive engagement are particularly deleterious for students' educational outcomes. We found that the *Moderately Disengaged* profile, characterized by engagement indices close to or below the mean, was consistently associated with the lowest science achievement across all three grades. Also as expected, the *Moderately Engaged* profile, characterized by all engagement indices above the mean, was associated with higher science achievement, supporting the importance of endorsing multiple dimensions of engagement in science learning for optimal academic performance (e.g., van Rooij et al., 2017; Wang & Peck, 2013). Thus, the patterns identified among our Moderately Disengaged and Moderately Engaged profiles and student science achievement replicate findings from past studies, showing that higher engagement in school is associated with bettter, and low engagement in school is associated with worse academic performance.

We also contribute the literature by presenting three unique subgroups of disengaged students that are differentially related to science achievement, providing a more nuanced look at how disengagement in science manifest among middle school students. The negative association between the *Disengaged* profile and science achievement warrants a closer look due to the shape effects identified in this profile. As noted previously, our *Disengaged* profile was distinct from disengaged profiles identified in prior studies due to the extreme indicators (the behavioral and global engagement indicators fell approximately 1 to 2 *SD* below the mean) and unique configurations across indicators (students also reported moderately high cognitive engagement) that characterized this profile. It seems that the negative consequences of being behaviorally and globally disengaged may exert a stronger influence that supersedes the potential benefits of simultaneously being cognitively engaged in science learning. However, it is important to note that the small size of the *Disengaged* profile may be contributing to the extreme variability across the indicators. Further research is needed to better understand this small subgroup of students who are consistently identified in engagement profile studies.

The negative relationship between behavioral disengagement and science achievement was also found for students in the *Behaviorally Disengaged* profile, who also demonstrated low science achievement. Although students in this profile simultaneously endorsed moderate affective engagement, here again, the lack of behavioral connection to science learning seemed to more negatively impact students' science outcomes. It is also possible that, students' interest and emotional connection to science learning (affective engagement) demonstrated in the *Behaviorally Disengaged* profile may protect against some of these negative effects, as the *Behaviorally Disengaged profile* was associated with better performance relative to the *Disengaged* and *Moderately Disengaged* profiles. Scholars have suggested that particularly during the formative adolescent years, students' affective connection to learning (e.g., sense of belonging, interest) is critical for optimal academic and psychological functioning (Wang & Peck, 2013).

Taken together, our findings suggest that a more differentiated approach to identifying and addressing the needs of students who are disconnected from science learning is needed. In particular, it may be important to identify whether students' disengagement is characterized by a lack of behavioral connection to learning (Behaviorally Disengaged, Disengaged) or overall disengagement across all dimensions (Moderately Disengaged), as these profiles are differentially associated with science achievement.

7.4. Limitations and directions for future research

Some limitations should be noted. First, with the exception of science achievement, we used self-report questionnaires. Although students' self-perceptions are appropriate measures for the constructs examined in this paper (e.g., Azevedo, 2015; Fredricks, Wang, et al., 2016; Usher & Pajares, 2008), future research is needed to gather additional estimates of students' engagement in real-time by using methods such as experience sampling methods, direct observations, and/or informant (e.g., teacher) reports. Second, the achievement outcome examined in this study focused on students' understanding of grade-level science content. Future research is needed to examine outcome variables such as self-regulation strategies and mastery of science disciplines beyond content knowledge (e.g., skills specific to scientific inquiry). Additionally, we examined the relationship between engagement profiles and mean science achievement outcomes using the BCH distal outcome procedure across three proximally related science achievement domains (Asparouhov & Muthén, 2014); however, future research is needed to examine to what extent engagement profiles predict science outcomes above and beyond the profiles by controlling for relevant predictors and profile indicators. Third, the *Disengaged* profile was very small is size, and although it provided substantive value in the interpretation of our five class solution, future research is needed to better understand the nature of profiles of students who lack engagement in school, as this profile is consistently identified in engagement profile studies but also consistently small in size (van Rooij et al., 2017; Wang & Peck, 2013). Fourth, the item variances were constrained equal across the profiles, and it is possible that significantly different variance estimates in one or more of the profiles could result in a different profile solution. More research is needed to understand how to appropriately handle fixed versus freely estimated variances in the context of person-centered analyses. Finally, future engagement profiles studies accounting for a global engagement indicator, as well as a recently proposed dimension of social engagement (Fredricks, Wang, et al., 2016), is needed in other grade levels, in different subject areas, and among student populations from different countries and education systems to test whether our findings can be generalized.

8. Conclusion

Research has converged on the construct of engagement as a key contributor to students' academic success. Results from this study contribute to the literature by accounting for a global engagement factor in the estimation of the latent profile solutions using a well-established three-part engagement framework (Fredricks et al., 2004), studying engagement profiles among a diverse sample of middle school students, and examining the profiles in relation to key motivation variables and science achievement. Findings provide important implications for our understanding of student engagement in science. First, in addition to replicating the *Moderately Engaged* and *Moderately Disengaged* profiles from prior studies (e.g., van Rooij et al., 2017; Wang & Peck, 2013), we identified three unique profiles characterized by qualitatively different configurations of low engagement that were differentially associated with students' science achievement. Additionally, in line with prior theoretical and empirical work, mastery goals and self-efficacy showed to be significant predictors of the likelihood of membership in the more highly engaged profiles. Our findings indicate that it may be important to take more differentiated approaches to addressing students' disengagement in diverse middle school classrooms, and our results point to specific motivation factors (mastery orientation and self-efficacy) that may hold promise for achieving these goals.

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Appendix A. Summary of previous person-centered studies of engagement profiles

Study	Sample	Engagement variables	Additional variables included in profiles	Number of profiles	Labels of the profiles	Relations with outcomes
van Rooij et al. (2017)	669 grade 12 students in the Netherlands	Behavioral engagement, cognitive engagement	Need for cognition, self-efficacy	5	(1) Intellectually highly disengaged, (2) Behaviorally and cognitively disengaged, (3) Overall average engaged, (4) Intellectually engaged, and (5) Overall engaged	GPA: 5 > 3 > 4 > 2 > 1 ECTS: 5 > 4 > 2 > 3 > 1 Academic Adjustment (overall): 5 > 3 > 4 > 1 > 2 Motivation: 5 > 4 = 1 > 3 > 2 Application: 5 > 3 > 4 > 1 > 2 Performance: 5 > 3 > 4 > 2 > 1 Environment: 5 > 4 > 3 > 1 > 2
Salmela-Aro et al. (2016)	443 high school students in the United States and Finland	School work engagement (composite factor score from energy, absorption, dedication subscales)	Three indices of school burnout: exhaustion, cynicism, and inadequacy	4	(1) Engaged, (2) Engaged-exhausted, (3) Moderately burned out, and (4) Burned out	(For U.S. group) Situational resources: 1 > 2 > 3 > 4 Situational demands: 1 < 2 < 3 < 4 Situational engagement: 1 > 3 > 2 > 4
Tuominen-Soini and Salmela-Aro (2014)	979 high school (1st and 3rd year) students in Finland	School work engagement (composite factor score from energy, absorption, dedication subscales)	Three indices of school burnout: exhaustion, cynicism, and inadequacy	4	(1) Engaged, (2) Engaged-exhausted, (3) Cynical, (4) Burned-out	School value: 1 > 2 > 3 > 4 Stress: 3 < 1 < 2 < 4 Fear of failure: 1 < 3 < 2 < 4 Academic withdrawal: 1 < 2 < 3 < 4 Work avoidance: 1 < 2 < 4 < 3 Academic achievement: 1 > 2 > 3 > 4 Self-esteem: 1 > 3 > 2 > 4 Depressive symptoms: 1 < 3 < 2 < 4
Wang and Peck (2013)	1025 grade 9 students in the United States	Behavioral engagement, affective engagement, cognitive engagement	N/A	5	(1) Moderately engaged, (2) Engaged, (3) Minimally engaged, (4) Emotionally disengaged, and (5) Cognitively disengaged	GPA: 2 > 4 > 1 > 5 > 3 Educational Aspiration: 2 > 1 > 5 > 4 > 3 Dropout College: 2 = 5 < 4 < 1 < 3 Enrollment Rates: 2 > 1 > 4 > 5 > 3 Depression: 2 < 5 < 1 < 3 < 4

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2019.101753.

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