A Person-Centered Approach to Understanding Adolescents' Reading Motivation and Its Relation to Reading Outcomes

Samira Syal[a], Marcia Davis[b], Xiaodong Zhang[a], Jason Schoeneberger[a], Samantha Spinney[a], Douglas J. Mac Iver [b], and Martha Mac Iver [b]

[a]ICF, Reston, VA, U.S.; [b]Johns Hopkins University, Baltimore, MD, U.S.

Correspondence concerning this article should be sent to Samira Syal (email: samira.rajeshsyal@icf.com)

Note: This article was made possible by the Institute of Education Sciences, U.S. Department of Education, through Grant R305A180154 to the Johns Hopkins University. The opinions expressed are those of the authors and do not represent views of the Institute or the U.S. Department of Education.

Abstract

Motivation to read is crucial to improving reading skill. While there is extensive research examining reading motivation among elementary students, with respect to adolescents, research is limited. Employing a person-centered approach can aid in developing a better understanding of adolescent reading motivation and would help address possible barriers to engaging adolescent readers. The present study extracted reading motivation profiles in a sample of 367 high school students based on their responses on the Adaptive Reading Motivation Measure (ARMM). Three profiles emerged—high (HRM), ambivalent/neutral (ARM), and low reading motivation (LRM)—where students in the HRM profile performed better on the reading achievement assessment and reported reading more often compared to their peers in the other profiles. Results shed light on key facets of adolescent reading motivation, which have implications for addressing motivational barriers to engaging adolescent readers.

Keywords: Reading Motivation, Latent Profile Analysis, Reading Achievement, Adolescents

A Person-Centered Approach to Understanding adolescents' Reading Motivation and Its Relation to Reading Outcomes

Recent international and national literacy assessments highlight the increasingly concerning state of adolescent literacy in the United States. For instance, the Organization for Economic Cooperation and Development (OECD)'s Programme for International Student Assessment (PISA) 2018 revealed that the average reading scores for 15-year-olds have remained relatively unchanged since 2000 (OECD, 2020). Interestingly, results from the National Assessment of Educational Progress(NAEP) 2019 indicate that Grade 12 reading scores have been steadily decreasing over the years, with 30% scoring below basic and 31% scoring at proficiency levels. These trends in adolescent literacy may be attributed to complexities associated with reading skills required at that age, where reading proficiency involves more than mere word reading and fluency tasks. Indeed, to be competent readers, not only are adolescents required to be adept at decoding and fluency, which can be foundational to basic comprehension tasks, they must also be able to understand and integrate text structures that take on many forms, as in the case of argumentation, scientific, or narrative text structures (Goldman & Snow, 2015; Kim et al., 2017). As such, the onus is on the adolescent to willingly engage in complex reading tasks.

Student motivation and engagement are frequently cited as barriers to adolescent literacy (e.g., Kamil et al., 2008) perhaps because literacy instruction may not necessarily incorporate strategies that motivate and engage adolescents (Kim et al., 2017). Engaging adolescents in reading can be beneficial to improving reading proficiency, especially since reading skill and motivation appear to have a recursive and cumulative effect on each other (e.g., McGeown et al., 2015; Morgan & Fuchs, 2007; Schiefele & Schaffner 2016). Motivated readers tend to read more and tend to expend more cognitive effort on challenging texts; thus, becoming more competent readers

(Barber & Klauda, 2020; Guthrie et al., 2004). Indeed, this recursive relationship has the potential to exacerbate "Matthew Effects" in reading because less-skilled readers tend to be less inclined to engage in necessary reading practice than their skilled counterparts; thus, becoming less-competent readers than skilled readers (Snow, 2017; Stanovich, 2009). However, research examining adolescent literacy is limited given that a large majority of research focuses on strategies to engage early readers (Conradi et al., 2014). As such, findings from this body of research reveal that motivation to read decreases with age (Anderman & Mueller, 2010), with older adolescents being less likely to view reading skill as useful, important, and valuable (Wolters et al., 2014).

The Reading and Motivation Relationship

Successful comprehension of texts is a prerequisite to academic success in adolescence. However, comprehension is a complex endeavor involving the construction of meaning from texts and integrating it with information from the reader's knowledge base (Kintsch & Rawson, 2008). To successfully comprehend texts, readers must be able to decode words, parse text structures to derive meaning at the sentence level and integrate meaning back to the text base and to the reader's prior knowledge to arrive at a situation model, or a mental representation, of the text (Cain & Oakhill, 2012). Less-skilled adolescent readers can have challenges at any juncture of this process (Biancarosa & Snow, 2004; Brasseur-Hock et al., 2011). Furthermore, adolescents are exposed to a wide array of texts (e.g., narrative or scientific texts) that have their own inherent challenges. For instance, scientific texts tend to have a high frequency of technical vocabulary that can require readers to expend substantial effort to decode (Ray & Meyer, 2011), thus impacting their ability to derive an overall situation model of the text and integrate that model with their prior knowledge. Comprehending scientific texts can also be inherently challenging because of the nontemporal and spatial ways their logical-argumentative text structures are organized (Ragnarsdóttir et al., 2002). Comprehension of texts can also be challenged by characteristics of the text medium, with digital texts requiring readers to expend considerable cognitive effort to derive a situational model because of extraneous features, such as brightly lit screens and scrolling, that can hinder the process of coherence-building needed for successful comprehension (Evans et al., 2009; Mangen & Kuiken, 2014; Singer & Alexander, 2017).

Evidence from a considerable body of research supports the finding that reading skill and motivation are related to each other. Not only is higher reading skill linked to higher motivational beliefs, but motivation is also associated with improved reading competence (Morgan & Fuchs, 2007). Several empirical studies contend that this reading-motivation relationship exerts cumulative and reciprocal effects on each other, where less-skilled readers are less likely to engage in the practice necessary to improve reading competence; thus, exacerbating reading difficulties (Snow, 2017). Indeed, studies have demonstrated that it is particularly advantageous to engage readers as it can mitigate gaps in reading difficulties and results in cognitive spinoffs where motivated readers tend to become more proficient readers because they read more, are likely to exert more cognitive effort on challenging texts, and use more reading strategies (Guthrie & Wigfield, 2000; Guthrie et al., 2004). In turn, their increasing proficiency can serve to motivate them to read more often and to engage in challenging reading tasks out of their own volition. This recursive relationship can exacerbate “Matthew Effects” in reading proficiency between skilled readers and their less-skilled peers since skilled readers become more skilled and the less-skilled do not improve (Snow, 2017; Stanovich, 2009).

Reading Motivation in Adolescence

Reading motivation has been defined as "the individual's personal goals, values, and beliefs with regard to the topics, processes, and outcomes of reading" (Guthrie & Wigfield, 2000, p. 405). Reading motivation differs at the individual level (Conradi et al., 2014), and can be contingent upon context (e.g., at home versus school; Guthrie et al., 2012).

Current research suggests that students' motivation to read tends to decrease with age. Anderman and Mueller (2010) found that motivational beliefs and attitudes toward reading decline during the transition from elementary school to middle school. Wolters et al. (2014) observed similar declines when examining motivational beliefs of adolescents, where younger adolescents were more likely to perceive reading as more valuable and useful to reach their academic aspirations compared to their older peers. Specifically, decreases in motivation were observed with male students in comparison to female students (McGeown et al., 2015) and students from minority racial and ethnic groups (Guthrie & McRae, 2012). One reason for this decline could be that as students transition from elementary school to middle school and subsequently to high school, there is an increasing focus on nonfiction texts that are more challenging to comprehend. Despite increasing reading challenges and declining motivation, there is limited research on understanding adolescent reading motivation. Indeed, the review by Conradi et al. (2014) notes that only 9% of reading motivation research involves adolescent readers. Although researchers are in agreement that reading motivation is a multidimensional and complex construct comprising a multitude of motivation constructs contextualized to the reading domain, there is little agreement on the nature and number of dimensions to be included (e.g., Conradi et al., 2014; Davis et al., 2018; Neugebauer & Fujimoto, 2020; Schiefele et al., 2012). For instance, Schiefele et al. (2012) posit that reading motivation comprises *intrinsic* and *extrinsic* reasons to read. Furthermore, they posit that motivational concepts such as interest and efficacy should not be subsumed under intrinsic motivation since they are inclined to be antecedents of reading where they shape the individual's inclination to read a given text. In the same vein, they posit that social aspects of reading are a form of extrinsic motivation where one's social contexts provide readers with incentives to read (e.g., recognition and competition). Conradi et al. (2014) argue that antecedents of reading motivation must be considered since they affect the reading task and are in turn affected by the reading task. Additionally, there appears to be some support for recognizing and leveraging shared values and the social context of reading to engage adolescent readers (Moje et al., 2008), necessitating the consideration of social motivation as independent of extrinsic reasons for reading (e.g., Conradi et al., 2014), particularly during adolescence when the social context is of prime importance. Developmentally, adolescence is a time for social discovery when students try to find who they are and where they fit in their world. Antonio and Guthrie (2007) leverage this need for social connection to engage adolescent readers since reading or nonreading can quickly become part of their identity. More recent conceptions of reading motivation recognize the importance of social motivation in reading constructs and recommend including it as a dimension of reading motivation (Conradi et al., 2014; Neugebauer & Fujimoto, 2020).

Measuring Adolescent Reading Motivation

Reading motivation measures tend to reflect the theoretical framework within which they were developed, which helps to explain variation across different scales (Conradi et al., 2014). According to the review by Davis et al. (2018), there are four scales targeting high school students. Although these scales have adequate reliability and validity as established in the review by Davis et al. (2018), they have not been used extensively, which is consistent with the limited research in this field. Moreover, these scales tend to be operationalized using singular motivational dimensions. For instance, the McKenna and Kear (1990) reading motivation measure, Survey of Adolescent Reading Attitudes, captures adolescents' reading-related attitudes, which they define as "acquired predispositions to respond in a consistently favorable or unfavorable manner with respect to aspects of reading" (p. 285). Another scale, the Reader Self-Perception Scale 2 (Henk et al., 2012), contains items that incorporate four factors of self-appraisals aligned with Bandura's self-efficacy theory: performance, observational comparison, social feedback, and physiological states. Motivation researchers argue that there are benefits to employing a multitude of constructs to capture the multidimensionality of reading motivation because it would offer a nuanced perspective of key factors that could potentially motivate—and conversely demotivate—readers (Conradi et al., 2014; Forzani et al., 2021; Guthrie & Coddington, 2009; Schiefele et al, 2012; Wigfield & Guthrie, 1995).

The scale used in this study is the Adaptive Reading Motivation Measure (ARMM; Davis et al., 2020), a computer-adaptive scale that was constructed to capture the multidimensionality of reading motivation specifically among adolescents. Reading motivation according to the ARMM is operationalized using items that measure goals, values, and beliefs contextualized to reading in an academic context. Initial research from Davis et al. (2020) provides evidence for a general reading motivation comprising the various dimensions included in the ARMM, indicating the possibility of a hierarchical structure where reading motivation is a higher-order latent construct subsuming the various related observed constructs.

Person-Centered Approaches to Reading Motivation in Prior Research

Although there is considerable evidence suggesting that reading motivation is multidimensional, studies employing person-centered approaches are few. Person-centered approaches help identify subgroups of individuals sharing specific attributes on a set of variables whereas variable-centered approaches examine relationships between variables. A person-centered approach for examining reading motivation in adolescence (that clusters people instead of variables) is beneficial to gaining a better understanding not only of how the different dimensions relate to each other but also of how individuals display varying patterns across dimensions. This may be useful to tailoring intervention efforts to the needs of the unique groups of individuals (e.g., Hayenga & Corpus, 2010; Roeser & Galloway, 2002). Research utilizing person-centered approaches yielded reading motivation profiles that vary widely, both in the number of profiles and in nature. For instance, Baker and Wigfield (1999) utilized a cluster analysis to extract seven clusters that varied to some degree across dimensions. It must be noted that this study was driven by statistical findings and in essence was conducted to explore the initial multidimensionality of reading motivation. As a result, the number of members in some of the extracted clusters was somewhat small, making it challenging to draw conclusions about generalizability. A more recent person-centered study by Schiefele and Löweke (2017) used a Latent Profile Analysis (LPA) to extract four motivation profiles, namely *high intrinsic* (high on involvement and curiosity, low on recognition and competition), *high involvement* (high on involvement, low on the remaining dimensions), *high quantity* (high on all dimensions), and *moderate quantity* (low to moderate on all dimensions). Profile extraction was rooted in their reading motivation framework delineated in Schiefele et al. (2012), where they posit that reading motivation involves solely intrinsic and extrinsic reasons to read. Motivational concepts such as interest and efficacy were considered antecedents of reading because they have the potential to orient the individual toward the reading task. Moreover, extrinsic reasons for reading include social aspects that arise out of being compelled or incentivized to read (e.g., recognition). Often, person-centered approaches to develop reading motivation patterns are contingent on how reading motivation is conceptualized and operationalized. In the research described above, Baker and Wigfield (1999) included the construct of reading efficacy whilst Schiefele and Löweke (2017) did not. Both studies focused only on elementary students.

Reading motivation research involving adolescents employing a person-centered approach is in its early stages. A study by Quirk et al. (2020) involving 254 ninth-grade students from Hispanic/Latino(a) backgrounds obtained four reading motivation profiles, namely a *High* profile characterized by high motivation across dimensions, a *High Practical* profile characterized by moderate to high levels of motivation, an *Apathetic* profile with moderate to low motivation across dimensions, and a *Low* profile with low levels of motivation across dimensions. In yet another study (Griffin et al., 2022) involving high school students from Hispanic/Latino(a) backgrounds, three reading motivation profiles were extracted – an *Average* profile characterized by slightly above-average scores on reading self-concept and slightly below-average scores on reading attitude, an *Above Average* profile characterized by above-average scores on both reading self-concept (RSC) and reading attitude (RA), and a *High RSC-Low RA* profile characterized by the highest reading self-concept level and below-average reading attitude levels. From these studies, it must be noted that both studies explored reading motivation among a specific subgroup of adolescents exhibiting varying degrees of bilingualism, which poses a limitation to generalizability. Furthermore, a second argument relates to the differences in how reading motivation is conceptualized and subsequently operationalized. The scale used by Quirk et al. (2020) included items related to identity, autonomy support, utility value, and importance. Quirk et al. (2020) operationalized reading motivation based on Unrau and Quirk's (2014) definition in which reading motivation was defined as thoughts, beliefs, and self-perceptions that drive and sustain reading tasks. Griffin et al. (2022) operationalized reading motivation as reading-related self-concept and reading attitudes. Despite these considerations, by employing a person-centered approach these studies shed light on motivational patterns unique to adolescent readers.

The Current Study

Given that motivation to read declines with age as adolescents become less inclined than their younger counterparts to perceive reading as valuable and that reading skill and motivation are interrelated, engaging adolescents in reading may play a crucial role in improving reading proficiency. By employing a person-centered approach to the examination of adolescent reading motivation, it becomes possible to gain a better understanding of motivational patterns shared by specific subgroups of adolescents; the implications of such an understanding could be instrumental in designing reading interventions for adolescents, specifically for adolescents with low motivation to read. Initial research using a person-centered approach in examining adolescent reading motivation revealed motivational patterns where profile membership is based on the amount of reading motivation (e.g., high, moderate, and low) (Griffin et al., 2022; Quirk et al., 2020). However, adolescent reading motivation profiles in these studies were based on a limited number of reading motivation dimensions, e.g., reading-related self-concept and reading attitudes in Griffin et al. (2022). This study aims to examine motivational patterns among adolescent readers using a person-centered approach using a multidimensional reading motivation measure (i.e., ARMM; Davis et al., 2020). This study used LPA, a mixed-method clustering technique, to identify specific subgroups and their patterns across the multitude of reading motivation constructs. In addition to identifying specific motivation profiles of adolescent readers, this study explored the relationship between profile membership and two reading outcomes, namely reading performance on a standardized reading assessment and adolescents' reports of how frequently they read. Herein, this study has two goals:

(1) Extracting adolescent reading motivation profiles based on responses on the Adaptive Reading Motivation Measure (ARMM; Davis et al., 2020) using a person-centered approach and,

(2) Exploring the relationship between adolescents with diverse motivational profiles and reading performance and frequency.

These goals are exploratory because of limited research in the field of adolescent reading motivation and because person-centered research identifying subgroups of adolescent readers with specific motivation profiles is in its early stages. Contrary to the framework of Schiefele and Löweke (2017), we posit that there is more to reading motivation among adolescents than mere extrinsic and intrinsic reasons for reading. We expect the extracted profiles will reflect additional components and hypothesize that a significant relationship exists between profile membership and reading performance and frequency (with significant differences between the various emergent clusters).

Methods

Participants and Procedure

The sample consisted of 367 students recruited from Grades 9 and 10 from four high schools across the United States in California, New York, Connecticut, and Alabama. This sample was drawn from a larger Institute of Education Sciences-funded study, Accelerating Literacy for Adolescents (ALFA) Lab, which is a semester-long supplemental course for struggling readers involving strategic reading instruction and collaborative literacy activities. As a part of the larger ALFA Lab study, students were assigned to either the treatment condition, which involved these supplemental activities, or to the business-as-usual comparison condition, which used a regression discontinuity design (RDD; e.g., Cook & Wong, 2008). Treatment assignment was based on cut-offs on different pre-ALFA Lab reading assessment scores at each school. Since ALFA Lab is designed for the most-challenged readers, students in the sample included those in the treatment and comparison conditions. The sample considered for this study included students regardless of their treatment status. Table 1 presents demographic information about the participants.

<Table 1 about here>

Measures

Measures employed in this study included students' reading motivation, measures of how often they read, and their reading performance.

Reading Motivation

Students' reading motivation was assessed using the Adaptive Reading Motivation Measure (ARMM; Davis et al., 2020), which involved 45 items that measured adolescent reading motivation. The ARMM consists of 15 subconstructs with items ranging from 1 (*Not at all like me*) to 6 (*Exactly like me*). Appendix A contains definitions and sample items for all 15 subconstructs. The ARMM is a computer-based adaptive measure where students were given three items for each of the subconstructs. Three negative constructs were reversed to indicate a lack of the construct (e.g., lack of antisocial goals for reading). Although Davis et al. (2020) demonstrated that there was adequate variance for a bifactor model, scores from the higher-order general reading motivation factor solution were used in this study. The instrument exhibits adequate levels of both construct and criterion validity with internal reliability of subscales ranging from 0.70 to 0.84 and an internal reliability of 0.94. For further information on the scale, administration procedures, and scoring, see Davis et al. (2020).

Reading Frequency

Students completed 10 items, eight items of which were adapted from the Progress in International Reading Literacy Study 2011 (International Association for the Evaluation of Educational Achievement, 2011), measuring frequency of reading certain types of texts, and frequency of completing reading for homework or fun. The remaining two items asked students to rate how often they read on a computer or electronic device. Ratings were provided as follows: 0 – *Never or almost never*, 1 – *Once or twice a month*, 2 – *Once or twice a week*, 3 – *Every day or almost every day*. Reliability for the scale was found to be adequate (Cronbach's alpha = .75).

Reading Achievement

The Star reading test, a 10-minute computer adaptive test, was used as a measure of reading achievement. It includes 24 items extracted from a bank of over 1,000 multiple-choice items. The Star reading test assesses students' reading skills constituting measures of vocabulary knowledge and skills, comprehension strategies and constructing meaning, analyzing short literary texts, understanding the author's craft, and analyzing argument and evaluating text. Scores range from 0–1400. The Star reading assessment has been found to have adequate reliability and validity with Cronbach's alpha reliability and test-retest reliability both at 0.90 based on the Star norming sample (Research Foundation for Star Adaptive Assessments, 2020).

Statistical Analysis

To identify groups of students with various reading motivation profiles with different combinations of intrinsic, extrinsic, and social motivation along with self-efficacy, LPA (Bauer & Shanahan, 2007) was employed using the *mclust* package in R Studio (Scrucca et al., 2016; Rosenberg et al., 2019). LPA, a person-centered mixture modeling analysis, is an appropriate technique given that it allows for data-driven extraction of profiles aligned with theory. In general, LPA works under the premise that residual variance can be minimized by adopting a latent variable that is categorical wherein the sample exudes characteristics of this latent variable to varying degrees. In so doing, the assumption is that obtained subgroups of the sample are homogenous in terms of patterns of means, variances, and covariances of the categorical latent variable (Wardenaar, 2021). Typically, LPA allows for the examination of patterns arising from the differences and/or overlap between class-specific parameter estimates, which can in turn be used to define profiles, delineate characteristics of profile membership, and develop insight into underlying mechanisms (Sterba, 2013). Simply put, for an LPA that adequately fits the data, it can be observed that individuals within each subgroup or class are likely to have similar scores on the observed variables.

The goal of LPA is to identify profiles or classes in congruence with theoretical assumptions having adequate model fit (Marsh et al., 2009; Tofighi & Enders, 2008). Decisions related to identifying the number of profiles are made based on goodness of fit indices, such as log likelihood, Akaike information criterion (AIC), Bayesian information criterion (BIC), adjusted BIC (ABIC), bootstrap likelihood ratio test (BLRT); and based on model configurations with varying class-specific parameters. Smaller values on the AIC, BIC, and ABIC indicate improved model fit. The BLRT assesses improvements in neighboring models (e.g., 1-profile versus 2-profile models). Statistical significance is ascertained based on these to determine whether the k-class model (i.e., 2-profile model) significantly improved when compared to the k-1 class model (i.e., 1-profile model); thus, accepting the 2-profile model over the 1-profile model (Wang & Wang, 2012).

Since LPA is a flexible approach allowing for data-driven extraction, there is a tendency for resultant models to become increasingly complex, thus necessitating the use of criteria such as

BIC and integrated completed likelihood (ICL) to select a model that adequately meets the requirements for model fit and model complexity. In this study, extractions of profiles were done using both BIC, a commonly used index showing the most parsimonious model, and ICL, an integrated measure of several fit indices that can be more conservative than BIC (Bauer & Curran, 2004; Tein et al., 2013; Wardenaar, 2021). Next, we used BLRT and subsequent *p*-values to compare fitness indices between class-specific models. Finally, entropy—a measure of delineation or discrimination between emergent profiles, with values greater than 0.80 approaching 1—was considered (Clark, 2010).

Once meaningful profiles were extracted, we employed SPSS to examine the predictive utility of profile membership on reading achievement measured through performance on a reading assessment and reading frequency measured through student self-reports of how often they read.

Results

Table 2 shows the descriptive statistics and intercorrelations between all motivational and reading outcome variables. No extreme outliers were observed (i.e., +/- 3SD) and skewness and kurtosis were satisfactory, with values between -2 and +2 (Hair et al., 2022) for all variables indicating that all variables were approximately normally distributed.

<Table 2 about here>

Latent Profile Analysis

Given the exploratory nature of the first goal of this study, several models were estimated with different numbers of classes and model configurations with BIC and ICL fit indices used to extract latent profiles. Figure 1 shows the optimal number of clusters that can be extracted from the motivation constructs using BIC and ICL. Based on these graphs, it appears that the most optimal solution is one with a model configuration of variable volume, equal shape, equal orientation, and ellipsoidal distribution, with 1 cluster using ICL and 2 clusters using BIC. It is important to note that among the two selection criteria used, BIC is often the preferred tool and is used extensively in research given that ICL can be more conservative (e.g., Tein et al., 2013; Wardenaar, 2021). However, there appears to be sufficient variance to examine patterns for 3 and 4 clusters. Hence, subsequent measures to ascertain satisfactory model fit with optimal number of clusters were based model solutions for up to 4 clusters or profiles.

<Figure 1 about here>

Subsequently, a BLRT was used to compare model fit between various class-specific models. Model fit indices of the four solutions are presented in Table 3. The 3-profile solution was better fitting when compared to the 2-profile solution due to a significant BLRT value ($p < .001$), and lower AIC and BIC values. Although the 4-profile solution yielded somewhat lower AIC and BIC values, the resulting BLRT value was not statistically significant ($p = .503$). Moreover, the 4-class solution yielded a class size that was too small relative to the other classes (12 students; 13.37% of the sample), making it difficult to draw inferences; thus, having minimal substantial value. Furthermore, when comparing entropy values, all four models with varying number of classes yielded satisfactory entropy values (i.e., greater than 0.80). Taken together, the 3-class solution was ascertained as the best fitting model because of small AIC and BIC values, a satisfactory entropy value, and a significant BLRT. Therefore, the 3-class solution was considered the best fit to the data.

<Table 3 about here>

The resulting 3-profile solution, depicted in Figure 2, appears to have clearly delineated profiles emerge. Class 1 was composed of 56.1% of the sample ($n = 206$) and represents individuals with relatively average levels across the 15 subconstructs of the ARMM. Accordingly, this profile was referred to as “Ambivalent” because these students appear to be relatively neutral with respect to the various dimensions of reading motivation measured in this study. Class 2 was composed of 28.6% of the sample (*n* = 105) and was termed “High Reading Motivation” because it comprised students with relatively high levels on almost all motivation constructs. Class 3 was composed of 15.3% of the sample (*n* = 56) and was characterized by students with relatively low levels across almost all reading motivation constructs; thus, referred to as “Low Reading Motivation.” Students in all three profiles had average levels on two motivation constructs—competition and recognition.

<Figure 2 about here>

Relations among Profile Membership, Reading Achievement, and Reading Frequency

To demonstrate predictive utility of the emergent profiles extracted through LPA, this study examined the relationship between profile membership and two reading outcomes—reading achievement and reading frequency. To examine this relationship, one-way Analyses of Variance (ANOVAs) were employed, where profile membership was entered as the independent variable and reading achievement and reading frequency were entered as outcome variables.

Results from the first one-way ANOVA with reading frequency as the outcome revealed significant differences between the three profiles on reading frequency, $F(2,354) = 63.08$, $p < .001$, $\eta_p^2 = 0.26$. Bonferroni post hoc comparisons indicated that the mean reading frequency score for students in the Low Reading Motivation (LRM) profile ($M = 8.04$, SD= 4.69) was significantly lower than those in the Ambivalent or Neutral Reading Motivation (ARM) ($M = 13.45$, SD = 4.96) and High Reading Motivation (HRM) profiles ($M = 17.37$, SD = 5.09). Additionally, students in the HRM profile had significantly higher mean scores on reading frequency than those in the ARM profile. Simply put, students characterized as HRM tend to read more often than their peers characterized as ARM and LRM.

<Figure 3 about here>

Specific to reading achievement, results indicated significant differences between the three profiles, $F(2,294) = 11.81$, $p < .001$, $\eta_p^2 = 0.07$. Bonferroni post hoc comparisons indicated that the mean reading achievement score for students in the HRM profile (M = 864.58, SD = 276.82) was significantly higher than the LRM profile (M = 649.89, SD = 258.07) and those in the ARM profile (M = 726.46, SD = 264.48). Mean reading achievement scores did not significantly differ between students in the ARM and the LRM profiles. That is, students characterized as having an HRM profile tend to perform better at reading than students in LRM or ARM profiles.

<Figure 4 about here>

Discussion

In the present study, a person-centered approach using LPA was used to group adolescent readers based on similar reading motivation profiles. Three profiles emerged — ARM, with average levels across all motivation subconstructs, HRM, with high levels across most subconstructs, and LRM, with low levels across most subconstructs. Interestingly, students across all three profiles demonstrated similar patterns on two motivation constructs, competition and recognition, where they were at average levels. Profiles that were extracted were then examined in relation to students' reading outcomes, specifically their reading performance and their reading frequency to obtain a measure of predictive utility and whether the extracted profiles contribute to current understanding of reading motivation theory, specifically for adolescents.

The profiles extracted through the LPA are a manifestation of the theoretical framework upon which the ARMM was conceptualized and developed. Based on this framework, reading motivation is considered to constitute intrinsic and extrinsic motivation, social motivation, and reading efficacy. The three profiles extracted demonstrate patterns that are high, average, and low on these motivation dimensions for the most part. Similar profiles, with respect to the nature and number of profiles, emerged from Quirk et al. (2020) and Griffin et al. (2022) where profile membership among adolescent readers was based on the amount of reading motivation (e.g., high, moderate, and low). However, these studies extracted profiles based on a limited number of reading motivation dimensions. In Quirk et al. (2020), reading motivation was operationalized using identity, autonomy support, importance, and utility value, whereas Griffin et al. (2022) measured reading motivation using dimensions of reading-related attitudes and self-concept. Indeed, research using a similar person-centered approach on examining reading motivation tends to extract profiles rooted in the theoretical framework upon which the measures are based. Among the few studies that operationalize reading motivation as a multidimensional construct that intersects with readers' interests, values, goals, and beliefs (Conradi et al., 2014), profile membership varied widely based on the scale used (e.g., Guthrie et al., 2009; Schiefele & Löweke, 2017). For instance, Schiefele & Löweke (2017) used a person-centered approach guided by their reading motivation framework (Schiefele et al., 2012), where four profiles were extracted: *high intrinsic* (high on involvement and curiosity, low on recognition and competition), *high involvement* (high on involvement, low on the remaining dimensions), *high quantity* (high on all dimensions), and *moderate quantity* (low to moderate on all dimensions).

In this study, students characterized as being in the HRM profile displayed higher-than average estimates on all motivation concepts related to intrinsic motivation (i.e., curiosity, interest, involvement, challenge, value, and autonomy), reading-related efficacy (i.e., perceived difficulty of texts, a lack of reading avoidance, and self-efficacy), and social motivation (i.e., social motivation, prosocial goals, and a lack of antisocial goals). Similarly, students characterized as being in the ARM reading motivation profile and LRM profile displayed average and lower-than-average estimates on these reading-related motivation dimensions, respectively. An interesting finding that emerged from the extraction of latent profiles was that all three profiles displayed average levels on two extrinsic motivation constructs—competition and recognition. One reason for this finding could be because of the mode of measurement and theoretical framework upon which the ARMM is founded, which captures three extrinsic motivation constructs—recognition, competition, and grades. It could be that because of the adaptive nature of the ARMM, students across the three profiles had similar scores on recognition and competition, making it challenging to discern differences between the three profiles on the two constructs.

Another finding relates to the inclusion of social motivation, where students characterized with LRM, ARM, and HRM profiles demonstrated lower-than-average, average, and higher-than-average scores on the three social motivation scores indicating the degree to which social aspects of reading are valued by students across the three profiles. Given that social aspects of learning are crucial during adolescence (e.g., Ryan & Patrick, 2001), the finding that social motivation is low for students in the LRM profile indicates the likelihood that leveraging social motivation to engage LRM adolescent readers can be promising. This deviates from some conventional theories of reading motivation that do not consider social motivation as a genuine reading motivation dimension (e.g., Schiefele et al., 2012) and in some cases is considered a form of extrinsic motivation (Wang & Guthrie, 2004). Indeed, there is support for recognizing the shared values of reading as a reading motivation construct independent of extrinsic reasons for reading (e.g., Conradi et al.2014).

Findings from the current study revealed noteworthy relationships between emergent reading motivation profiles and reading outcomes, namely reading frequency and reading performance, where significant differences between adolescents across the three profiles were obtained. Specific to reading frequency, students characterized in the HRM profile reported reading significantly more than students in the ARM and LRM profiles, and students with the ARM profile reported reading significantly more often than students in the LRM profile. Furthermore, with respect to reading performance, students with an HRM profile scored significantly higher on the reading performance measure than students characterized by the ARM or LRM profiles. These findings are consistent with existing research findings that students with high reading motivation tend to have better reading achievement and tend to read more (Guthrie et al., 2009; Schiefele & Löweke, 2017). A reason for these findings could be due to the recursive nature of the reading and motivation relationship where motivated readers tend to spend more time reading and are likely to engage in reading practice; thus, improving reading proficiency. Subsequently, skilled readers tend to be more motivated to engage in reading tasks (Morgan & Fuchs, 2007).

Limitations and Future Directions

Despite the scarcity of person-centered approaches in adolescent reading motivation, the present study provides early evidence for deriving motivational profiles of adolescents in alignment with the ARMM constructs. Three motivational profiles were extracted based on class-specific patterns, namely high, ambivalent/neutral, and low reading motivation profiles. Furthermore, this study demonstrated the significant association between profile membership and reading performance and frequency.

When evaluating these findings, some limitations need to be considered. First, although this study employed a multidimensional scale meant for adolescent readers (i.e., the ARMM), which demonstrated evidence for a general reading motivation construct, Davis et al. (2020) demonstrated that there was sufficient unexplained variance remaining after the initial hierarchical solution. Indeed, they demonstrated that the bifactor *model* was better fitting in comparison. This suggests that perhaps further research is needed to reconceptualize reading motivation to gain insights into the structure and dimensionality of reading motivation. In doing so, a person-centered approach might reveal markedly different profiles. The second caveat relates to our use of the LPA. Because of the scarcity of person-centered research in the field and the lack of consensus surrounding the dimensions of reading motivation, decisions regarding optimal number of profiles were made based on model-fit indices. It remains to be seen whether the extracted profiles are appropriate representations of theory and, as such, can benefit from further research. Moreover, it is important to note that profile membership is probabilistic (Bauer & Curran, 2003), and, as such, further research is needed before conclusions of temporal stability can be drawn. Lastly, the sample included Grade 9 and 10 students from four high schools across the country, which poses generalizability issues when interpreting these findings.

Despite these shortcomings, the present study adds to extant literature by offering a deeper understanding of adolescents' reading motivation; the implications of such an understanding can be advantageous in designing and tailoring reading interventions for specific sub-groups of adolescents with varying levels of reading motivation. Indeed, there is some benefit to engaging adolescent readers given the link between reading motivation and reading competence. As such, findings from this study shed light on the role of social motivation. Specifically, the inclusion of social reading motivation indicates the potential for using social aspects of reading motivation in reading interventions as a tool to engage adolescent readers of varying motivation levels. Future investigations can focus on understanding the role of social motivation in engaging adolescent readers, especially those considered struggling. Given the reciprocal reading-motivation relationship, it stands to reason that incorporating elements that foster adolescent engagement in reading instruction can be advantageous to improving reading proficiency specifically for students in the LRM profile.

Acknowledgements

The work presented here was funded by the U.S. Department of Education's Institute of Education Sciences (R305A180154).

Declaration of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

References

Anderman, E. M., & Mueller, C. E. (2010). Middle school transitions and adolescent development. In *Handbook of research on schools, schooling, and human development* (pp. 198–215). Routledge.

Antonio, D. & Guthrie, J.T. (2007). Reading is social: Bringing peer interaction to the text. In J.T. Guthrie (Ed.), *Engaging adolescents in reading* (pp. 49–64). Corwin Press.

Baker, L., & Wigfield, A. (1999). Dimensions of children's motivation for reading and their relations to reading activity and reading achievement. *Reading Research Quarterly, 34*, 452–477. https://doi.org/10.1598/RRQ.34.4.4

Barber, A. T., & Klauda, S. L. (2020). How reading motivation and engagement enable reading achievement: Policy implications. *Policy Insights from the Behavioral and Brain Sciences*, *7*(1), 27–34. https://doi.org/10.1177/2372732219893385

Bauer, D. J., & Curran, P. J. (2003). Distributional assumptions of growth mixture models: implications for overextraction of latent trajectory classes. *Psychological Methods, 8,* 338–363. https://doi.org/10.1037/1082-989X.8.3.338

Bauer, D. J., & Curran, P. J. (2004). The integration of continuous and discrete latent variable models: Potential problems and promising opportunities. *Psychological Methods, 9*, 3–29. https://doi.org/10.1037/1082-989X.9.1.3

Bauer, D. J., & Shanahan, M. J. (2007). Modeling complex interactions: Person-centered and variable-centered approaches. In T.D. Little, J.A. Bovaird, & N.A.Card (Eds.), *Modeling contextual effects in longitudinal studies*, (pp. 255–83). Psychology Press.

Biancarosa, G., & Snow, C. E. (2004). *Reading next: A vision for action and research in middle and high school literacy.* Carnegie Corporation of New York.

Brasseur-Hock, I. F., Hock, M., Kieffer, M., Biancarosa, G., & Deshler, D. D. (2011). Adolescent struggling readers in urban schools: Results of a latent class analysis. *Learning and Individual Differences, 21*, 438–452. https://doi.org/10.1016/j.lindif.2011.01.008

Cain, K., & Oakhill, J. (2012). Reading comprehension development from 7 to 14 years: Implications for assessment. In J. P. Sabatini, E. Albro, & T. O'Reilly (Eds.), *Measuring up: Advances in how we assess reading ability* (pp. 59–76). Rowman & Littlefield.

Clark, S. L. (2010). *Mixture modeling with behavioral data*. University of California, Los Angeles.

Cook, T. D., & Wong, V. C. (2008). Empirical tests of the validity of the regression discontinuity design. *Annales d'Économie et de Statistique*, *91/92*, 127–150. https://doi.org/10.2307/27917242

Conradi, K., Jang, B. G., & McKenna, M. C. (2014). Motivation terminology in reading research: A conceptual review. *Educational Psychology Review*, *26*, 127–164. https://doi.org/10.1007/s10648-013-9245-z

Davis, M. H., Tonks, S. M., Hock, M., Wang, W., & Rodriguez, A. (2018). A review of reading motivation scales. *Reading Psychology, 39,* 121–187. https://doi.org/10.1080/02702711.2017.1400482

Davis, M. H., Wang, W., Kingston, N. M., Hock, M., Tonks, S. M., & Tiemann, G. (2020). A computer adaptive measure of reading motivation. *Journal of Research in Reading, 43*, 434–453. https://doi.org/10.1111/1467-9817.12318.Evans, M. A., Charland, A. R., & Saint-Aubin, J. (2009). A new look at an old format: Eye tracking studies of shared book reading and implications for eBooks and eBook research. In A. G. Bus & S. B. Neuman (Eds.), *Multimedia and Literacy Development: Improving Achievement for Young Learners* (pp. 89–111). Routledge.

Forzani, E., Leu, D. J., Yujia Li, E., Rhoads, C., Guthrie, J. T., & McCoach, B. (2021). Characteristics and validity of an instrument for assessing motivations for online reading to learn. *Reading Research Quarterly*, *56*(4), 761–780. https://doi.org/10.1002/rrq.337

Goldman, S. R., & Snow, C. E. (2015). Adolescent literacy: Development and instruction. In A. Pollatsek & R. Treiman (Eds.), *The Oxford handbook of reading* (pp. 463–478). Oxford University Press.

Griffin, R. A., Mindrila, D., & Farran, L. K. (2022) Latent profiles of reading motivation in adolescent native-Spanish-speaker multilingual learners. *Reading Psychology, 43*, 151–178. https://doi.org/10.1080/02702711.2021.2008073

Guthrie, J. T., & Coddington, C. S. (2009). Reading motivation. In K. Wentzel & A. Wigfield (Eds.), *Handbook of motivation at school* (pp. 503–526). Routledge.

Guthrie, J. T., Coddington, C. S., & Wigfield, A. (2009). Profiles of reading motivation among African American and Caucasian students. *Journal of Literacy Research*, *41*, 317–353. https://doi.org/10.1080/10862960903129196

Guthrie, J. T., & McRae, A. (2012). Motivations and contexts for literacy engagement of African American and European American adolescents. In J. T. Guthrie, A. Wigfield, & S. L. Klauda (Eds.) *Adolescents' engagement in academic literacy*. (pp. 216–294).

Guthrie, J. T., & Wigfield, A. (2000). Engagement and motivation in reading. In M. L. Kamil, P. B. Mosenthal, P. D. Pearson, & R. Barr (Eds.), *Handbook of reading research* (vol. 3, pp. 403–422). Lawrence Erlbaum Associates Publishers.

Guthrie, J. T., Wigfield, A., Barbosa, P., Perencevich, K. C., Taboada, A., Davis, M. H., Scafiddi, N. T., & Tonks, S. (2004). Increasing reading comprehension and engagement through concept-oriented reading instruction. *Journal of Educational Psychology*, *96*, 403–423. https://doi.org/10.1037/0022-0663.96.3.403.

Guthrie, J. T., Wigfield, A., & You, W. (2012). Instructional contexts for engagement and achievement in reading. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.) *Handbook of research on student engagement* (pp. 601–634). Springer Science + Business Media.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.

Hayenga, A.O & Corpus, J.H. (2010). Profiles of intrinsic and extrinsic motivations: A person-centered approach to motivation and achievement in middle school. *Motivation and Emotion, 34*, 371–383. https://doi.org/10.1007/s11031-010-9181-x.

Henk, W. A., Marinak, B. A., & Melnick, S. A. (2012). Measuring the reader self-perceptions of adolescents: Introducing the RSPS2. *Journal of Adolescent & Adult Literacy, 56*, 311– 320. https://doi.org/10.1002/Jaal.00144.

Kamil, M. L., Borman, G. D., Dole, J., Kral, C. C., Salinger, T., & Torgesen, J. (2008). *Improving adolescent literacy: Effective classroom and intervention practices: A practice guide* (NCEE #2008-4027). National Center for Education Evaluation and Regional Assistance, Institute of Education Sciences, U.S. Department of Education. https://ies.ed.gov/ncee/wwc/docs/practiceguide/adlit_pg_082608.pdf

Kim, J. S., Hemphill, L., Troyer, M., Thomson, J. M., Jones, S. M., LaRusso, M. D., & Donovan, S. (2017). Engaging struggling adolescent readers to improve reading skills. *Reading Research Quarterly*, *52*, 357–382. https://doi.org/10.1002/rrq.171

Kintsch, W. & Rawson, K. A. (2008). Comprehension. In M.J. Snowling & C. Hulme (Eds.), *The science of reading: A handbook* (Vol. 9, pp. 209–226). John Wiley & Sons.

Mangen, A., & Kuiken, D. (2014). Lost in an iPad: Narrative engagement on paper and tablet. *Scientific Study of Literature*, *4*(2), 150–177. https://doi.org/10.1075/ssol.4.2.02man

Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. (2009). Classical Latent Profile Analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling: A Multidisciplinary Journal*, *16*(2), 191–225. https://doi.org/10.1080/10705510902751010

McGeown, S. P., Duncan, L. G., Griffiths, Y. M., & Stothard, S. E. (2015). Exploring the relationship between adolescent's reading skills, reading motivation and reading habits. *Reading and Writing, 28,* 545–569. http://dx.doi.org/10.1007/s11145-014-9537-9.

McKenna, M. C., & Kear, D. J. (1990). Measuring attitude toward reading: A new tool for teachers. *Reading Teacher, 43*(9), 626–639.

Moje, B. E., Overby, M., Tysvaer, N., & Morris, K. (2008). The complex world of adolescent literacy: Myths, motivations, and mysteries. *Harvard Educational Review*, *78*(1), 107–154. https://doi.org/10.17763/haer.78.1.54468j6204x24157

Morgan, P. L., & Fuchs, D. (2007). Is there a bidirectional relationship between children's reading skills and reading motivation? *Exceptional Children, 73*(2), 165–183. https://doi.org/10.1177/001440290707300203.

Neugebauer, S. R., & Fujimoto, K. A. (2020). Distinct and overlapping dimensions of reading motivation in commonly used measures in schools. *Assessment for Effective Intervention*, *46*(1), 39–54. https://doi.org/10.1177/1534508418819793.

Organization for Economic Cooperation and Development (OECD). (2020). *Programme for International Student Assessment (PISA): Results from PISA 2018.* https://www.oecd.org/pisa/publications/PISA2018_VolIV_USAcountrynote.pdf

Quirk, M., Swami, S., Loera, G., & Garcia, S. (2020). Latinx adolescents' reading motivation profiles and associations with higher education aspirations. *Literacy Research and Instruction, 59*, 218–293. https://doi.org/10.1080/19388071.2020.1752862.

Ragnarsdóttir, H., Aparici, M., Cahana-Amitay, D., van Hell, J., & Viguié, A. (2002). Verbal structure and content in written discourse: Expository and narrative texts. *Written Language & Literacy, 5*(1), 95–125. https://doi.org/10.1075/wll.5.1.05rag

Ray, M. N., & Meyer, B. J. (2011). Individual differences in children's knowledge of expository text structures: A review of literature. *International Electronic Journal of Elementary Education, 4*(1), 67-82. https://eric.ed.gov/?id=EJ1068612

Research Foundation for Star Adaptive Assessments (2020). *Science of Star* [White paper]. Renaissance. https://renaissance.widen.net/view/pdf/vfyzi55v1e/R14807.pdf?t.download=true&u=zceria

Roeser, R. W., & Galloway, M. G. (2002). Studying motivation to learn in early adolescence: A holistic perspective. In T. Urdan & F. Pajares (Eds.), *Academic motivation of adolescents: Adolescence and education* (pp. 331–372). Information Age Publishing.

Rosenberg, J. M., Beymer, P. N., Anderson, D. J., van Lissa, C. J., & Schmidt, J. A. (2019). tidyLPA: An R package to easily carry out Latent Profile Analysis (LPA) using open-source or commercial software. *The Journal of Open Source Software*, *3*(30), 978. https://doi.org/10.21105/joss.00978

Ryan, A. M. & Patrick, H. (2001). The classroom social environment and changes in adolescents' motivation and engagement during middle school. *American Education Research Journal, 38,* 437–460. https://doi.org/10.3102/00028312038002437

Schiefele, U., & Löweke, S. (2017). The nature, development, and effects of elementary students' reading motivation profiles. *Reading Research Quarterly*, *53*(4), 405–421. https://doi.org/10.1002/rrq.201

Schiefele, U., & Schaffner, E. (2016). Factorial and construct validity of a new instrument for the assessment of reading motivation. *Reading Research Quarterly*, *51*(2), 221–237. https://doi.org/10.1002/rrq.134

Schiefele, U., Schaffner, E., Möller, J., & Wigfield, A. (2012). Dimensions of reading motivation and their relation to reading behavior and competence. *Reading Research Quarterly*, *47*, 427–463. https://doi.org/10.1002/RRQ.030.

Scrucca, L., Fop, M., Murphy, T. B., & Raftery, A. E. (2016). mclust 5: Clustering, classification and density estimation using Gaussian finite mixture models. *The R Journal*, *8*(1), 289–317.

Singer, L. M., & Alexander, P. A. (2017). Reading on paper and digitally: What the past decades of empirical research reveal. *Review of Educational Research, 87,* 1007–1041. https://doi.org/10.3102/0034654317722961

Snow, C.E. (2017). Motivation and engagement in language and literacy development. In E. Segers & P. van den Broek (Eds.), *Developmental perspectives in written language and literacy* (pp. 137–148). John Benjamins Publishing Co.

Stanovich, K. E. (2009). Matthew Effects in reading: Some consequences of individual differences in the acquisition of literacy. *The Journal of Education, 189,* 23–55.

Sterba, S. K. (2013). Understanding linkages among mixture models. *Multivariate Behavioral Research*, *48*(6), 775–815. https://doi.org/10.1080/00273171.2013.827564

Tein, J. Y., Coxe, S., & Cham, H. (2013). Statistical power to detect the correct number of classes in Latent Profile Analysis. *Structural equation modeling: A multidisciplinary journal*, *20*(4), 640–657. https://doi.org/10.1080/10705511.2013.824781

Tofighi, D., & Enders, C. K. (2008). Identifying the correct number of classes in growth mixture models. In G.R. Hancock & K.M. Samuelson (Eds.), *Advances in latent variable mixture models*, *2007* (pp. 317–341). Information Age Publishing.

Unrau, N. J., & Quirk, M. (2014). Clarifying the distinction between reading motivation and reading engagement. *Reading Psychology, 35*, 260–284. https://doi.org/10.1080/02702711.2012.684426

Wang, J. H.-Y. & Guthrie, J. T. (2004). Modeling the effects of intrinsic motivation, extrinsic motivation, amount of reading, and past reading achievement on text comprehension between U.S. and Chinese students. *Reading Research Quarterly, 39*, 162–186. https://doi.org/10.1598/RRQ.39.2.2

Wang, J., & Wang, X. (2012). Mixture modeling. In J. Wang & X. Wang (Eds.), *Structural equation modeling: Applications using Mplus* (pp. 289–391). Wiley.

Wardenaar, K. (2021). Latent Profile Analysis in R: A tutorial and comparison to Mplus. *PsyArXiv*. https://doi.org/10.31234/osf.io/wzftr..

Wigfield, A., & Guthrie, J. T. (1995). Dimensions of children's motivations for reading: An initial study. *Reading Research Report, 34*. http://files.eric.ed.gov/fulltext/ED384010.pdf.

Wolters, C. A., Denton, C. A., York, M. J., & Francis, D. J. (2014). Adolescents' motivation for reading: Group differences and relation to standardized achievement. *Reading and Writing*, *27*, 503–533. https://doi.org/10.1007/s11145-013-9454-3.

Appendices

Appendix A: Definition and Sample Items of the Adaptive Reading Motivation Measure (ARMM)

Construct	Definition	Sample Item
Perceived difficulty (R)	Belief that reading is hard or problematic	The books that teachers assign are often hard for me to read
Self-efficacy	Sense that one can accomplish reading tasks	I am one of the best readers in my class
Autonomy	Perception that one has some control over one's reading choices	Choosing what I want to read is important to me
Social motivation	Reading in order to feel connected with others	I like to talk with my friends about what we read in class
Prosocial goals	Desire to help, cooperate, or follow rules of the classroom related to reading	I like to help my classmates understand what they have read
Antisocial goals (R)	Desire to not help, to avoid interaction, or to make fun of others regarding reading	My friends and I laugh at classmates who do not read well
Reading avoidance (R)	Deliberately avoiding texts or minimizing effort when reading in school	I find ways to avoid reading in class
Grades	Pursuit of high reading grades in school	Getting good grades in reading is important to me
Competition	Desire to outperform others in reading	It's important to me that I read better than my classmates
Recognition	Pursuit of recognition for success in reading	I feel proud when I am recognized as a good reader
Involvement	Deep engagement with a text	I get so involved in my reading that I often lose track of time
Interest	Personal preferences toward reading certain topics	I have favorite topics I like to read about

Construct	Definition	Sample Item
Value	Belief that reading is important, relevant, or useful	It’s very important to read a lot
Challenge	Preference for reading relatively difficult or challenging texts	I enjoy reading difficult material
Curiosity	Desire to read in order to learn more about new topics	I get excited when reading about new things

Note. Constructs with (R) indicated that Items reverse coded so that scores indicate lack of the construct

Tables

Table 1

Demographic Information of the Sample

Variable	*n*	Percentage
Gender		
Female	181	49.32%
Male	186	50.68%
Grade		
Grade 9	212	57.77%
Grade 10	155	42.23%
Race		
Asian	7	1.91%
Black/African American	69	18.81%
Hispanic/Latino(a)	243	66.21%
White	22	5.99%
Multiracial	11	2.99%
Did not respond	15	4.09%

Table 2

Descriptive Statistics and Correlations of the Study Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Perceived Difficulty	-																
2. Self-efficacy	.533**	-															
3. Reading Avoidance	.447**	.568**	-														
4. Social Motivation	.095	.451**	.417**	-													
5. Prosocial Goals	.174**	.544**	.467**	.730**	-												
6. Antisocial Goals	.394**	.367**	.597**	.295**	.353**	-											
7. Grades	.379**	.760**	.672**	.717**	.750**	.472**	-										
8. Competition	.108*	.485**	.247**	.401**	.421**	.049	.578**	-									
9. Recognition	.193**	.578**	.419**	.466**	.546**	.201**	.701**	.627**	-								
10. Autonomy	.199**	.528**	.419**	.508**	.502**	.306**	.686**	.322**	.504**	-							
11. Involvement	.304**	.684**	.606**	.660**	.655**	.435**	.900**	.450**	.561**	.650**	-						
12. Interest	.382**	.760**	.684**	.728**	.745**	.474**	.993**	.550**	.674**	.698**	.913**	-					
13. Value	.325**	.677**	.604**	.655**	.642**	.429**	.919**	.483**	.567**	.622**	.842**	.929**	-				
14. Challenge	.398**	.703**	.601**	.658**	.644**	.359**	.887**	.503**	.549**	.582**	.805**	.902**	.823**	-			
15. Curiosity	.309**	.658**	.635**	.676**	.682**	.437**	.908**	.466**	.557**	.586**	.835**	.924**	.858**	.847**	-		
16. Star Score	.323**	.340**	.207**	.066	.130*	.158**	.259**	.133*	.132*	.225**	.306**	.264**	.248**	.255**	.190**	-	
17. Reading Frequency	.157**	.387**	.373**	.470**	.431**	.242**	.571**	.219**	.272**	.428**	.576**	.596**	.603**	.564**	.594**	.092	-
Mean	46.76	46.49	44.72	49.79	51.50	46.08	47.38	50.38	46.17	45.66	46.78	47.41	46.96	48.89	49.50	755.78	13.79
Standard Deviation	9.35	10.58	9.27	10.45	10.10	8.81	10.56	11.29	11.26	11.31	10.01	10.62	10.99	10.71	10.71	276.85	5.77
Skewness	.02	-.02	.23	-.30	-.40	.20	-.07	-.01	-.08	-.02	-.03	-.07	.09	-.16	-.32	.05	-.11
Kurtosis	.21	.73	.77	-.23	.59	.50	1.15	.31	.19	.29	1.11	1.16	.65	.88	.69	-.34	-.42

$^{*}p < .05$; $^{**}p < .01$

Table 3

Latent Profile Analysis: Model Fit Indices with Varying Numbers of Profiles

Solution	BIC	AIC	Entropy	BLRT (*p*)
1 Class	15784.65	15667.49	1.00	-
2 Class	13628.38	13628.38	0.92	64.04 (.001)
3 Class	12744.92	12502.79	0.95	59.74 (.001)
4 Class	11686.26	11990.88	0.84	30.65 (0.503)

Note. BIC = Bayesian Information Criterion; AIC = Akaike Information Criterion; BLRT = Bootstrap Likelihood Ratio Test.

Figures

Figure 1

Number of Components Extracted using Bayesian Information Criterion (BIC) (Left) and Integrated Completed Likelihood (ICL) (Right)

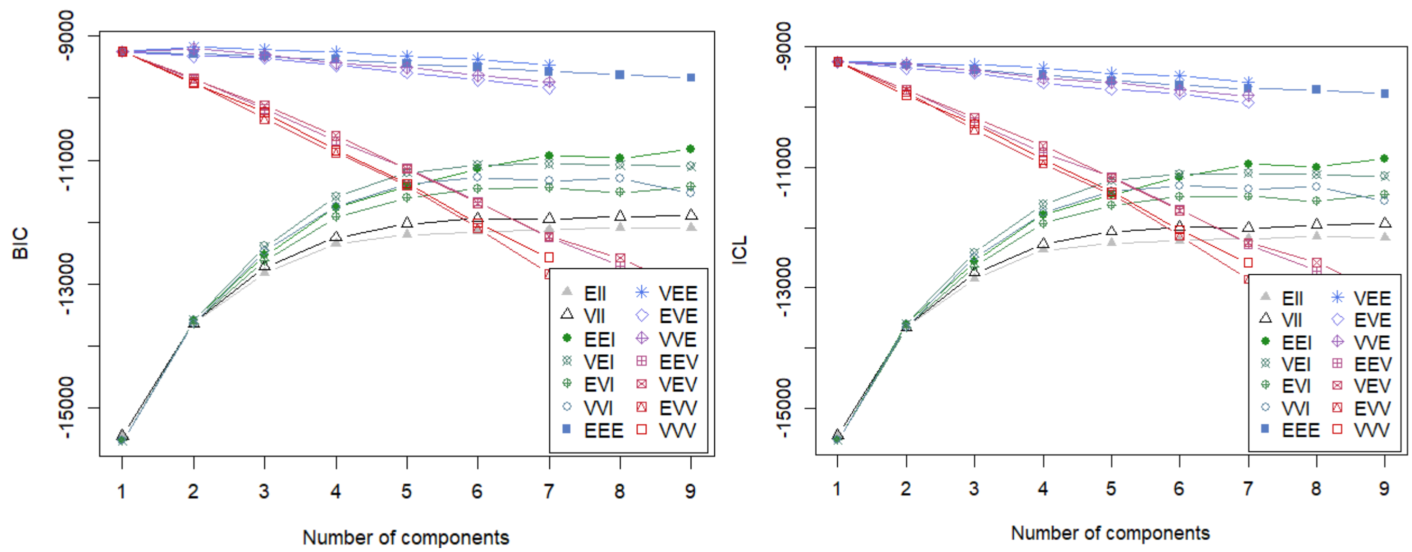

Figure 2

Extracted Reading Motivation Profiles

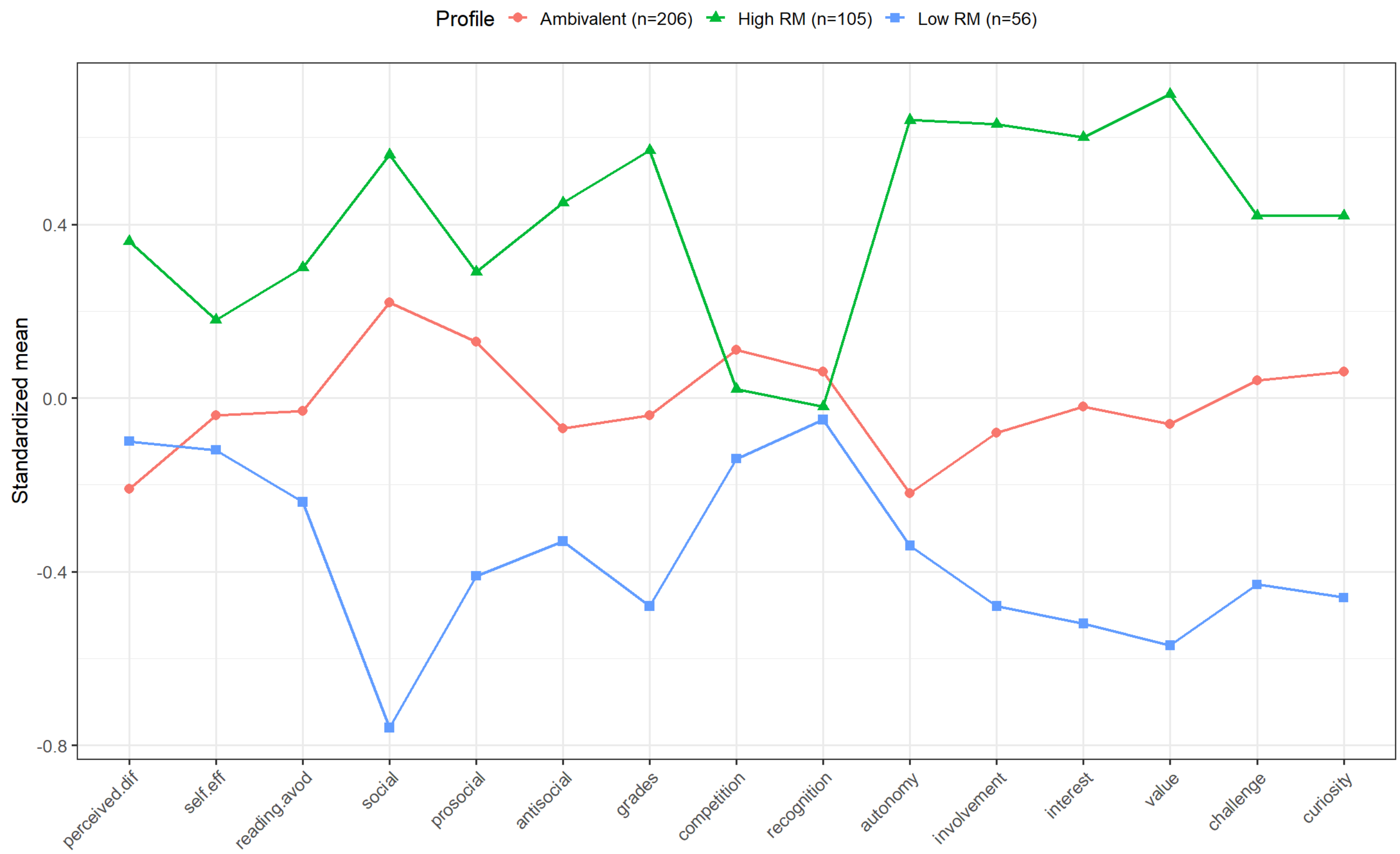

Figure 3

Differences between Profiles on Reading Frequency

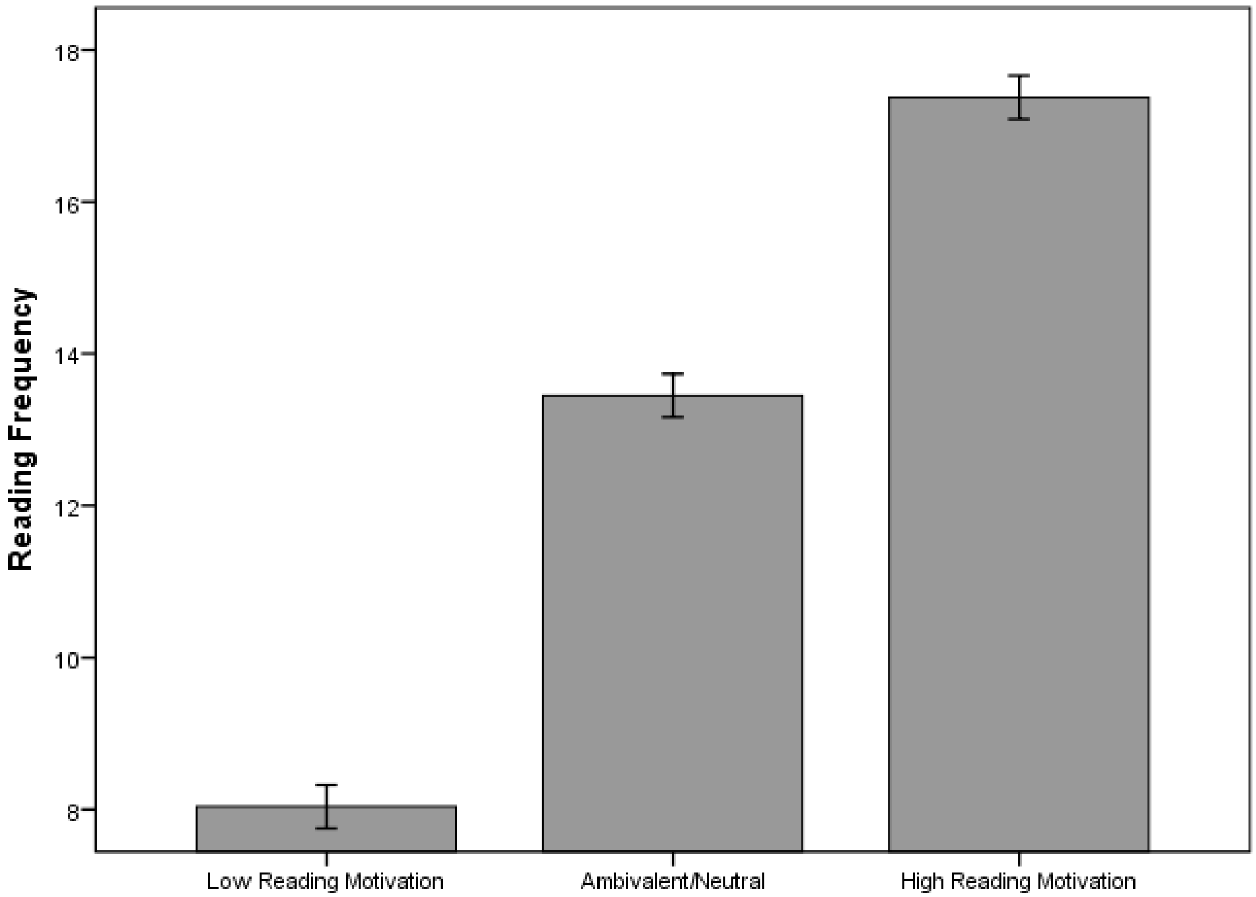

Figure 4

Differences Between Profiles on Reading Achievement