THE IMPACTS OF STUDENT-LEVEL AND SCHOOL-LEVEL FACTORS ON STUDENTS' READING ACHIEVEMENT: AN APPLICATION OF HIERARCHICAL LINEAR MODELING

By

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ABSTRACT

Reading achievement of students is one of the most significant predictors of their academic performance and competitiveness in society. Researchers have been investigating the reading achievement related factors for decades from different aspects. This study aimed to examine relevant factors that are associated with reading achievement from both the student and school levels. The student-level factors included English language proficiency (ELL), students' reading motivation, and students' home resources. The school-level factors included school SES, teacher's characteristics, school literacy readiness, and grade-level reading proficiency. A large-scale data set of 3,001 fourth-grade students from 133 elementary schools in the United States was included in the current study. The dataset was part of the Progress in International Reading Literacy Study (PIRLS) 2016 international public database. Considering the nested structure of the dataset, Hierarchical Linear Modeling (HLM) was utilized to analyze the impacts of student- and school-level predictors on the fourth-grade students' reading achievement simultaneously. The results indicated that the factors at student level were all significantly predicting reading achievement. The inclusion of student-level predictors reduced 8.3% of the total variance in reading achievement. The results also showed that school SES and grade-level reading proficiency were significant predictors of reading achievement at school level, whereas the later predictor demonstrated extremely weak predictive capacity in the prediction. The variations in the intercepts of different schools were explained by school-level factors and the vast majority of the 13% of the total variance in reading achievement was accounted for by school SES. In addition, the full model with both student- and school-level predictors made significant improvement compared to the unconditional model and student-level model by providing the best model-fit. The educational implications for improving reading achievement and limitations were discussed as well.

Keywords: Reading achievement; Student-level factors; School-level factors; Hierarchical linear modeling.

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CHAPTER I

INTRODUCTION

It was true in the past and even more so now that reading achievement serves as an essential component for individuals in contemporary society. Reading proficiency is not merely a basic school-based skill but also a functional necessity in daily life (Linnakyla, Malin, & Taube, 2004). It has been suggested that early reading achievement is a significant and reliable predictor of students' later academic achievement (Duncan et al., 2007). Similarly, findings suggest that students who have reading deficits in the elementary grades continue to struggle with reading throughout their entire school careers (Carlson & Francis, 2002). Likewise, students who are underachieving in literacy are more likely to drop out of school, struggle to find adequate employment, and earn less money over their lifetimes (Carlson, 2013). Being a proficient reader empowers students to think critically; to make connections between their own experiences and the exterior world; and to access, analyze, and evaluate the information they have received (Braunger & Lewis, 2006). Thus, proficient reading achievement is a valuable skill not only in school settings but also in one's future career.

Over the last decades, parents, educators, researchers, and policy makers have expressed concerns about U.S. students' reading proficiency along with how to effectively improve reading achievement. For example, Scammacca et al. (2016) looked back over the last 100 years at the efforts that have been made to improve reading achievement of struggling readers through reading interventions and they believe that the researchers and practitioners will gain better achievements over the next century.

Similarly, Torgesen (2002) also found that it is a process filled with both challenges and pleasures for those people who committed themselves to promote reading achievement or to take responsibilities in related areas among school-age students because the results turned out that school education did not reach the expected goal in teaching students to read. According to the latest National Assessment of Educational Progress (NAEP, 2019), the average reading achievement score of 2019 at fourth-grade level fell significantly from NAEP's 2017 achievement score. The data showed that only 35% of fourth-grade students performed at or above the proficient level in reading. Nonetheless, reading scores of fourth-grade students in 2019 were higher than those when reading was examined for the first time in 1992. While this improvement may seem promising, a vast majority of students (65%) did not achieve proficient scores in 2019 (NAEP, 2019).

Despite decades of effort, the percentage of students who reached the advanced literacy level has shown negligible improvement since testing began in 1992. Therefore, it is particularly important to continually study the possible factors that may affect reading achievement in order to implement targeted instruction to promote students' reading achievement (Lynch, 2002). The factors that have a great impact on reading achievement can be classified into several different categories, such as students' cognitive ability, individual characteristics, teacher-level factors, and school-level indicators. This study focused on the factors from the student and school levels.

Reading Achievement and Students' Characteristics

It has been suggested that students' background characteristics are significant contributors to the variance in reading achievement (Netten, Droop, & Verhoeven, 2010) and some student-level factors are highly correlated with students' reading achievement

(Goodwin, 2000). The main body of research on differences in reading achievement among students deals with individual difference issues. Children are innately different from one another and they exhibit tremendous variation in reading performance (Share, Jorm, Maclean, & Matthews, 1984). Not surprisingly, researchers have devoted themselves to identifying individual differences in reading achievement from different aspects of students' characteristics (Baker & Wigfield, 1999; Geske & Ozola, 2008; Smith, Smith, Gilmore, & Jameson, 2012). Variables that are related to student level include ethnic and language background (Abedi, 2002), reading motivation (McKenna, Kear, & Ellsworth, 1995; Partin & Hendricks, 2002), and home resources (Goldenberg, Rueda, & August, 2006; Hoff, 2013).

The relationship between language proficiency and reading achievement is one of the most prevailing issues being discussed by reading specialists due to the literacy gaps between English language learners (ELLs) and non-ELLs. The latest available report from NAEP (2019) shows a significant gap between ELL and non-ELL students in reading proficiency: the non-ELL students achieved 33 points higher than ELLs in reading achievement at fourth-grade level. The difference was even greater for older students. The non-ELL students achieved 45 points higher than ELLs in reading achievement at eighth-grade level. The critical link between reading achievement and language proficiency indicates the continual need to address ELL students' language skills.

Moreover, understanding the relationship between motivation and reading achievement is another critical factor when investigating students' reading performance. Motivation makes reading an interesting activity and proficient readers often possess reading motivation (Roberts, Torgensen, Boardman, & Scammacca, 2008). Conversely, if a student lacks motivation to read a complex text, they will not attempt to read or even comprehend the text, thus negatively affecting their reading performance (Morgan & Fuchs, 2007). One of the essential factors for reading success is motivation because it drives students to engage in frequent reading practice and to extract meaning from what they read (Barber & Klauda, 2020). Motivated readers often show a spontaneous interest in activities, enjoy the process of learning, and have a sense of accomplishment with success (Unrau & Schlackman, 2006).

In addition, research indicates stakeholders should also consider students' home resources regarding reading proficiency. The number of studies amid the relationship between home resources and reading achievement presents an increasing trend of concerns (Sirin, 2005; Strand & Schwippert, 2019). For example, it has been found that the number of books at home significantly predicts students' reading achievement and students who come from a low educational-level family benefit more from the book investment at home (Evans, Kelley, & Sikora, 2014). Understanding the relationship between home resources and reading outcomes is essential because it demonstrates the disparate impact that individual literacy environments can have on students from varying households (Kieffer, 2011).

Reading Achievement and School Accountability

Coleman and his co-authors' work *"Equality of Educational Opportunity*" (1966) has inspired those interested in school accountability for students' academic achievement for half a century and it is still being developed and discussed contemporarily (Hanushek & Raymond, 2005). Raudenbush and Bryk (1986) advocated that the essence of educational research is to test hypotheses about the impacts that school-level factors produce on school processes. In the past decades, both academic researchers and the U.S. government have performed extensive research to examine the impact of school accountability on reading achievement.

There is a growing concern about students' reading proficiency in the last decade and people have regarded students' nationwide reading deficits as a literacy crisis (Jacobs, 2008). The No Child Left Behind Act of 2001 (NCLB) recognized the importance of literacy skills and elevated reading ability to a high priority. The mission of the act is to enable all students to become successful readers. The Reading First initiative, a part of the NCLB Act, established a $6 billion investment to guarantee the high-quality and targeted reading instructions in order to promote reading performance of young children (U.S. Department of Education, 2003). The NCLB Act focuses on increasing book-access activities through Literacy Through School Libraries program. They aim to improve students' reading achievement by holding schools and states accountable. All the actions mentioned above fully demonstrated that the federal government has attached great importance and placed a primary emphasis on school accountability for students' reading development.

The function of school supports in preventing students from undesirable academic achievement has drawn attention from policy-makers, researchers and educators in the last decades as well (e.g., Garmezy, 1993). Wentzel and Looney (2007) proposed that schools undertake high responsibilities in the process of students' academic life by generally providing students with learning environments. Recent research also showed that quality of schooling resulted in real differences in academic earnings and attainment

(Hanushek & Raymond, 2005). Similarly, Van Hek, Kraaykamp, and Pelzer (2018) indicated that although schools demonstrate great influences on students' academic performance, the degree of influence is completely different for individual students.

A large amount of literature has discussed the association between school characteristics and reading achievement, such as school SES (Armor, Marks, & Malatinszky, 2018; Marks, 2015), teacher's characteristics (Wayne & Youngs, 2003), school literacy readiness (Antilla, 2013), and academic emphasis of school at grade level (Strickland, 2013). The current study aimed to explore several factors at both the student and school levels in order to comprehensively understand the differences of reading achievement among students.

Hierarchical Linear Modeling

Hierarchical linear modeling (HLM) helps researchers explore the impacts of the independent variables at different levels on the outcome variable. As there are predictor variables from two different levels involved in the current study, it is necessary to know the history and existing research of HLM method so that researchers are able to build better understanding of HLM and its contribution in educational area.

HLM is a commonly used statistical method for nested data (e.g., students nested in classrooms) when the predictor variables are defined at hierarchical system as well as characterizing individuals and groups (Woltman, Feldstain, MacKay, & Rocchi, 2012). Snijders and Bosker (2012) argued the variability exists not only between lower levels (e.g., students) but also between higher levels (e.g., class and school level). The general concept of a hierarchical problem is to investigate the relationships between variables that are generated at different hierarchical levels (Hox, Moerbeek, & Schoot, 2017). Thus, each level within a hierarchical structure can be conceptualized by its own submodel, and all of these models indicate the relationships (inside a given level) among the variables of interest (Raudenbus & Bryk, 2002).

People's social tendency is to interact with the environment they belong to and the interactive relationship usually demonstrates reciprocal influence on one another (Hox, Moerbeek, & Schoot, 2017). Hierarchical structures of nested data are common data types in many areas, such as organizations, schools, and clinics (Osborne, 2000). For example, in educational settings, students are nested in a higher-level classroom or school (the lowest level is usually defined as the individual) and their characteristics are influenced by higher-level groups. As stated in Julian (2001), "the data collected from students are not just a function of the interrelations and processes specific to the individual level—they are also influenced by the myriad of systems operating at the classroom and school levels" (p. 326).

The majority of educational research neglects the importance of a hierarchical dataset and fails to estimate these factors (Ma & Klinger, 2000). In hierarchical structure where data is nested, it is necessary to take the nesting phenomenon into account when the nesting structure potentially influences predicting variable effects on outcome variables (Anderson & Brown, 2010). Failure to consider hierarchical structure of nested data can lead to "aggregation bias, misestimated standard errors, and heterogeneity of regression" (Raudenbush & Bryk, 2002, p. 5). In the past, when researchers were dealing with nested data, they had no choice but to rely on regular regression (Huta, 2014). However, the problem that the nested data has is the violation of independence assumption required by the linear regression (Peugh, 2010; Raudenbush & Bryk, 2002).

Thus, the common influence from the higher-level factors on student performance causes problems because the statistical models also assume that the residuals are independent from each other. For example, it is difficult to accurately estimate both the student and school characteristics without considering the hierarchical feature of educational data (Raudenbush & Willms, 1991). In addition, with inaccurate estimation of student and school factors, teachers, educators, and school administrators may make inaccurate decisions on student diagnosis and evaluation (Snijders & Bosker, 2012).

Purpose of the Study and Research Questions

When it comes to reading achievement, the particular and enormous variations among students must be recognized (Share, Jorm, Maclean, & Matthews, 1984). It is relatively easy to spot differences among students concerning their reading levels and proficiency within a single school, but it’s hard to address between-school reading achievement variation. As current literature indicates, the differences in reading achievement among students at school level have become a prevailing phenomenon in the last decades (Chatterji, 2006). Conducting research to explore students’ reading achievement differences with different levels of factors could enable researchers to identify student reading problems more accurately (Share, Jorm, Mackean, & Matthews, 1984). For the current study, the following student-level factors were included: language proficiency (ELL), reading motivation, and home resources. School-level factors contained school SES, teacher’s characteristics, school literacy readiness, and grade-level reading proficiency. Given the hierarchical structure of the data (students nested within schools), HLM was applied in order to incorporate the issues related to correlation among reading achievement, student-level factors, and school-level factors.

The primary objective of the current study was to examine and explore the impacts of some determinants at student level and school level on reading achievement by analyzing the Progress of International Reading Literacy Study (PIRLS) data in 2016 from representative fourth-grade samples of 133 elementary schools in the U.S. According to Casey (2010), fourth-grade is the transitional stage of a student from learning to read to reading to learn. Starting from fourth grade, students apply the foundational reading skills that they have mastered to gain more information through reading independently in different subjects. Fourth grade is also the time period that students begin to think critically about the material they read. In conclusion, reading proficiency at fourth grade can be regarded as a significant indicator of a student's later educational development.

HLM could be utilized to analyze the specific student-level factors along with the school-level factors on fourth-grade students' reading achievement in the U.S. First, we examined whether student characteristics (e.g., ELL, reading motivation, home resources) were related to reading achievement. Second, we explored whether the amount of variation in different types of school characteristics (e.g., school SES, teacher's characteristics, school literacy readiness, and grade-level reading proficiency) were related to students' reading achievement. A better and more comprehensive understanding of the influence at both the student and school levels on reading achievement may explain the achievement gaps among students.

Specifically, this study examined the following questions (RQ):

1. Does the fourth-grade students' reading achievement vary across schools?

2. To what extent are student-level factors (e.g., ELL, students' motivation, and home resources) related to reading achievement at the fourth-grade level when school-level random effect is accounted for?
3. To what extent are school SES, teacher's characteristics, school literacy readiness, and grade-level reading proficiency related to the fourth-grade students' reading achievement?

CHAPTER II

LITERATURE REVIEW

This chapter provides a review of research on reading achievement and its related variables of interests at both the student and school levels. In addition, it is important to understand the development, history, as well as the theoretical framework of HLM. The review of literature also collects the educational research which applies the statistical technique of HLM on reading achievement at different levels (e.g., student level, teacher level, school level, and country level) and interprets their findings. Finally, this section describes the specific details of model building along with the model interpretation.

Student-Level Predictors on Reading Achievement

English language learners. Reading achievement related issues of English language learners (ELLs) are such an important focus of research because of the drastically increasing ELL population in the U.S. public schools (August, McCardle, & Shanahan, 2014). ELLs refer to the group of people who come from non-English-speaking homes and backgrounds and at the same time need to learn English as another language through specialized services in order to use it as a tool to effectively and fluently communicate (Slavin & Cheung, 2005). According to the latest count from National Center for Education Statistics (NCES, 2018), the percentage of public school ELLs in the United States was around 4.8 million (approximately 9.5 % of the school population). It has been predicted by some demographers that the percentage of ELLs will increase tremendously and could be as high as 20% by 2030 (Farbman, 2015). A mass of research has persistently revealed that ELLs almost always exhibit reading deficits and problems compared to their proficient peers due to the hurdles of English language proficiency (e.g., Klingner & Vaughn, 1996). In light of educational policy, the predictive ability of language proficiency has been widely discussed for the purpose of better learning outcomes and stronger accountability of ELLs (Genesee, Lindholm-Leary, Saunders, & Christian, 2005). Meanwhile, the discussion about how long it takes through endless efforts (special language programs and services) to get rid of the label of ELLs and the influence of language proficiency on reading achievement of students has become a mainstream in education area (e.g., Grant, Gottardo, & Geva, 2011; Jongejan, Verhoeven, & Siegel, 2007).

Studies showed that ELL students lagged behind their monolingual counterparts on reading tasks (e.g., reading comprehension, fluency, and oral language skills), and the reading achievement gap is less likely to be closed in a limited amount of time (Crosson & Lesaux, 2009; Hutchinson, Whiteley, Smith, & Connors, 2003; Nakamoto, Lindsey, & Manis, 2007). The reports from NAEP (2019) have shown that the average reading score of students who are identified as ELLs is significantly lower than that of non-ELLs at both fourth-grade (191 vs. 224) and eighth-grade levels (221 vs. 266). Reading achievement gaps between ELLs and non-ELLs have been steady without changes since reading proficiency of ELLs was first measured in 1998. Mancilla-Martinez and Lesaux (2010) proposed that ELLs do not master adequate language skills from English exposure at school to attain an equivalent achievement in vocabulary and reading comprehension as non-ELLs do. The gap between ELLs and non-ELLs concerning academic achievement is expected because first language acquisition is a natural process, which occurs at an early time of individuals' lives through family interactions, conversations, early school, as well as social activities (Hakuta, Butler, & Witt, 2000). Therefore, it will be extremely challenging for ELLs to catch up with their native-speaker peers concerning language proficiency in a short time.

Reading motivation. Reading proficiency remains an insurmountable barrier for many struggling readers even though endless efforts through research and teacher instruction have been attempted. However, researchers continue investigating this difficult problem by studying as many factors as possible that affect reading, including reading motivation of students.

Wigfield and Guthrie (1997) proposed that reading motivation is a multidimensional latent trait of students, despite significantly predicting reading capacity and breadth. The researchers identified a positive relationship between reading motivation and reading achievement based on evidence from laboratory and classroom observation for decades (Wigfield, Gladstone, & Turci, 2016). Research results clearly indicated that reading motivation remains the strongest predictor of the hobby of reading when the other variables are controlled (Guthrie & Cox, 2001). Reading researchers have investigated reading motivation from several different constructs, such as reading attitude, intrinsic and extrinsic motivation, and frequency of practicing reading. The current study examined reading motivation from two aspects: reading attitude and reading frequency.

Reading attitude refers to readers' intuitive feeling and interest in reading. The feeling of reading is an approach to measure individuals' willingness to read and how likely it is for readers to get actively engaged in reading; thus, attitude is highly related to students' reading motivation (Alexander & Filler, 1976). McKenna and Kear (1990) reported in their survey that the relationship between reading achievement and reading attitude remains robustly strong through sixth grade. Classroom reading instructors are confident with the significant impact of students' reading attitude on their reading achievement (Russ, 1989). Pajares and Schunk (2001) found that difficulties in reading process motivate high-attitude students to overcome the challenges with various strategies, thereby transferring the challenges into a sense of achievement.

The emphasis of reading attitudes of students is also placed on grade level and it demonstrates some differences. For example, Petscher (2010) presented a moderate correlation between reading attitudes and achievement at the primary school level (.44) and a lower correlation at middle school level (.24). It has been suggested that teachers and parents need to address students' negative feelings about reading in a timely manner (Martinez, Aricak, & Jewell, 2008).

In addition, children's reading quantity and frequency make significant contributions to reading motivation in elementary school (Wigfield & Guthrie, 1997). Not surprisingly, it has been found that there is a positive correlation between total reading time and reading achievement as well as the significant enhancement of the perception of the world (Guthrie & Cox, 2001). Reading frequency significantly predicts students' proficiency in the domains of reading comprehension and vocabulary acquisition (Stanovich, 1986); thus, encouraging students to get involved in reading activities with a positive attitude frequently becomes a main focus of teachers' reading instruction (De Naeghel, Van Keer, Vansteenkiste, & Rosseel, 2012). Furthermore, research results illustrated that reading amount plays a role of regulation in the relationship between reading attitude and reading achievement (Becker, McElvany, & Kortenbruck, 2010). Consequently, the relationships among reading attitude, reading frequency, and reading achievement cannot be dismissed lightly because the reciprocal influence has been obtained (Guthrie, Wigfield, Humenick, Perencevich, Taboada, & Barbosa, 2006). They concluded that reading motivation contributes to the amount and breadth of their readings so that students enjoy interacting with what they are reading about. Research has further revealed that more positive attitudes are associated with more successful achievement, and more time invested in reading is leading to better reading performance (Thames & Reeves, 1994).

Home resources. Given the predictive ability of early reading achievement on later academic achievement, people begin to explore the contributions of multiple factors and their correlations to reading outcomes. Therefore, they give rise to home literacy environment related factors (e.g., Alston-Abel & Berninger, 2018; Siriboe & Harfitt, 2018). There is no unique concept to define what an effective home literacy environment is for students; however, it generally refers to the number of books and reading materials to read for information and the number of learning equipment in the household (Huang, Tse, Chu, Xiao, Lam, Ng, & Hui, 2019).

The application and effectiveness of digital technologies in promoting the reading capacity of students has been discussed in the last two decades at both school and home settings (Casey & Bruce, 2011; Johnson, 2010; Barone & Wright, 2008). The discussions over the relationship between computer use and reading achievement are conflicting. For example, in the work of Rosen and Gustafsson (2016), they conducted a longitudinal study to investigate the relationship between computer availability at home and reading achievement for fourth-grade students and the results showed that the use of a computer at home produced negative impacts on students' reading achievement.

However, Barber (2006) observed positive impacts of computer use at home on students' reading achievement.

Saracho (1997) emphasized the importance of reading materials at home, which perform as the primary indicator of home literacy environment affecting children's early literacy achievement. For example, Morni and Sahari (2013) pointed out that the number of books at home is a reflection of family reading culture and it has a substantial effect on children's reading attitude and interest. In other words, lacking reading materials at home may affect the development of children's positive attitude towards reading and delay children's reading attainment and literacy acquisition.

In Huang and his colleagues' work (Huang, Tse, Chu, Xiao, Lam, Ng, & Hui, 2019), they examined the correlation between home literacy environment (e.g., the number of books at home and the amount of time that students spent reading at home) and students' reading attainment. The findings revealed that the number of books at home as well as the amount of time that students spent reading at home significantly and positively impact students' reading achievement and progress. Tse (2012) proposed that students' success in literacy at school can't be achieved without extensive reading and abundant reading materials at home. Evidence has also shown that the results of high-quality home reading resources are equivalent to a school-based "pull-out program" concerning the influence on reading achievement (Evans, Shaw, & Bell, 2000). Similarly, Tarelli and Stubbe (2010) claimed that the relationship between home resources and students' reading achievement is robustly stable because high-income parents are more likely to afford and invest money in purchasing digital technologies (e.g., tablet, computer), books, reading materials and internet access. In other words, students are more likely to gain opportunities and resources to get engaged in reading activities and obtain more support from good quality of home literacy environment than those who come from families with limited home reading resources.

School-Level Predictors on Reading Achievement

School SES. The relationship between socioeconomic status (SES) and academic achievement is not supposed to be only limited to home SES. It has been suggested that the positive correlation between school SES and students' academic performance is a common phenomenon in almost all countries (e.g., Armor, Marks, & Malatinszky, 2018; Langenkamp & Carbonaro, 2018; Opdenakker & Van Damme, 2001). Sirin (2005) pointed out in his meta-analyses that school SES has an even more profound influence on students' academic performance than home SES does.

The study indicated that students in the higher-SES schools gain better academic performance than students in the lower-SES schools when their social backgrounds do not differ too much (Perry & McConney, 2010). In addition, Perry and McConney (2013) also compared the relationship between school SES and students' learning outcomes in reading and mathematics of Australia and Canada. The results revealed that school SES is highly correlated to students' reading and mathematics performance in both countries regardless of their individual SES and their academic achievement improved when school SES increased.

Lee and Burkam (2002) proposed that there is a strong correlation between school SES and students' learning outcomes in regard to teachers' quality and resource quality. For example, higher-SES schools are more likely to recruit higher-quality teachers, to enroll higher-achieving students, and to provide better resources (Hansen, Rosen, &

Gustafsson, 2004). Teachers in some low-SES schools contribute relatively less time in delivering reading instruction to students than teachers from high-SES schools, which is highly related to students' reading outcomes (Greenwood, Arreaga-Mayer, & Carta, 1994). In addition, teachers from low-SES schools do not devote their time seeking external help from digital techniques and abundant materials in reading instruction (Cooper & Speece, 1990).

In addition, school resources, which reflect another aspect of school SES, have demonstrated positive impacts on students' reading achievement. For example, students' access to a school library may promote interest in reading and help bridge the gap between affluent students who have a large number of books at home and economically disadvantaged students who lack books at home (Araujo & Costa, 2015). In conclusion, the variable of school SES grants further research into reading achievement.

Teacher's characteristics. Teachers are the primary resources in an education system, and students' achievement substantially relies on the assignment of teachers for each school (Wayne & Youngs, 2003). Teachers are always the primary concerns for policymakers and researchers when it comes to K-12 educational outcomes. For example, the research indicated that teachers' expectation is highly related to students' reading outcome by placing value in reading classrooms (Ouzts, 1982). In addition, Bradshaw and Hershfeldt (2012) indicated that efficacious teachers present a significant relationship with high-quality instruction as well as vibrant learning environment.

Reading instruction tends to be complex and difficult not only because the instruction needs to be tailored according to the needs of each specific grade and individual classroom, but also because reading instruction requires a collection of skills in terms of high-quality implementation (e.g., language art, reading, writing, and epistemological perspectives) (Shanahan, 1994). McCutchen and his colleagues (2009) suggested that teachers are supposed to be equipped with sufficient amount of linguistic knowledge when they aim to help the struggling and deficient readers concerning instruction effectiveness. Although reading teachers possess knowledge of reading to some extent, that does not necessarily imply that good readers can be good reading teachers to instruct students in reading with complexities (Venezky, 1979).

According to Blair, Rupley, and Nichols (2007), teachers' knowledge is an essential factor which accounts for the variances in students' reading success. Influential teachers put students' reading needs in priority and clearly know the importance of reading proficiency (McCutchen, Green, Abbott, & Sanders, 2009). Reading teachers play critical roles in creating reading environments and activities to motivate students to be fully involved in the text, and those scenarios require teachers' knowledge and experience (McLaughlin, 2012). Furthermore, Aikens and Barbarin (2008) emphasized the importance of a classroom-based reading environment with abundant reading materials and passionate reading teachers because teachers will inspire the students to interact with reading materials in order to improve their reading performance.

School literacy readiness. School literacy readiness tends to be another significant factor of reading achievement. According to Smith and Chapel (1970), reading readiness refers to "the time at which a child is capable of learning to read" (p. 59). Therefore, the definition of literacy readiness can be derived based on the definition provided by reading readiness, which indicates that students are supposed to master proficiency in the domains of reading, writing, listening, and speaking at an age-appropriate point and also need to demonstrate significant transitions from an illiterate to a literate status. Schifferdecker (2007) indicated that literacy readiness is a difficult yet worthy transition, which not only allows students to be proud of their changes in literacy performance but also lay a solid foundation for future reading achievement at school. It has been suggested that children entering kindergarten with lower literacy readiness will produce a sustained and larger gap concerning the later reading readiness and reading achievement. According to Morales (2010), students will have more difficulties in learning to read once they have insufficient pre-existing reading skills that developed at early ages. Weigel and Martin (2006) informed that literacy readiness is not only influencing later school achievement but also impacting the design of reading programs. Therefore, literacy readiness of students indirectly contributes to reading achievement.

Literacy readiness is an important sign of getting ready for school of children which harvests with support, and the research further indicates that literacy readiness at preschool period is conducive to reading achievement in the first three school years (grade one to grade three) (Walker, Greenwood, Hart, & Carta, 1994). Further, early literacy readiness is a significant predictor of students' later reading attitude (Lawson, 2012), and the relationship between reading attitude and reading achievement has been substantially demonstrated in the previous section. Research indicates that schools as well as teachers need to attach great importance to their choices for reading interventions for students who are entering with limited literacy skills (e.g., letter recognition, word reading, and sentence reading) in order to ultimately improve students' reading achievement (Antilla, 2013). Literacy readiness is strongly connected to reading attainment and is one of the important guarantees of future academic performance.

Grade-level reading proficiency. In order to promote students' academic achievement and to prepare them for college and career readiness, Common Core State Standards (CCSS) released consistent standards and explicit expectations for each grade in English language arts (ELA) for K-12 students across states in 2010 (National Governors Association Center for Best Practices & Council of Chief State School Officers, 2010). More than 41 states along with the District of Columbia have voluntarily adopted and implemented the standards as their state educational standards for ELA on the grade-level basis. One of the ultimate goals of K-12 grade-specific standards is to help students to better prepare for the expectations of higher-education institutions and a future career in terms of literacy performance. Strickland (2013) stressed the significance of grade-level standards which is for the purpose of out-of-classroom requirements in society.

The literature does not yield abundant results by searching for terms of "grade-level reading emphasis/grade-level reading instruction". The majority of the literature is based on CCSS documents and earlier state particular standards. Therefore, it becomes more crucial to explore the predictive ability of grade-level reading proficiency on reading achievement at the school level to inform policy makers and school educators of the impact of grade-level reading instruction. For example, students' poor performance in reading may not be due to their individual characteristics (e.g., home SES, school SES, home literacy environment), but because students at their particular grade level have not received corresponding and grade-appropriate instruction and exposure.

The CCSS documents have stated that, "students can only gain the reading foundation when the curriculum is intentionally and coherently structured to develop rich content knowledge within and across grades" (Common Core State Standards Initiative, 2010, p. 10). In addition, Allington (2006) has indicated that there is a negative correlation between the difficulty level of reading materials and reading achievement, which reveals the importance of the grade-appropriate reading instructions and materials. Students left behind in reading performance at grade level are more likely to have difficulties in comprehending the written content for the following learning process (Lesnick, Goerge, Smithgall, & Gwynne, 2010). The purpose of encouraging students to read at grade level is to help them keep pace with the increasing reading demands of later grades.

The Application of HLM in Reading Achievement

In the last decade, numerous studies have utilized HLM to identify the predictive ability of factors at different levels on reading achievement. The studies were selected based on three key words: reading achievement, HLM/multilevel analysis, and large-scale dataset. Fung and ElAtia (2015) investigated the relationship between the factors from student level (e.g., language proficiency, participation in discussion, parents' involvement), school level (e.g., school location, time amount of English language arts instruction), and reading scores through a two-level HLM model. The results suggested that all student-level factors were statistically significant in predicting reading scores and accounted for only 12% of the variance in the outcome variable. However, none of school-level factors demonstrated a statistically significant relationship with reading scores.

Klinger, Rogers, Anderson, Poth and Calman (2006) identified the relationship between student- and school-level factors and the performance on a literacy test using a two-level hierarchical model. The results indicated that all 14 student-level predictors (e.g., gender, amount of reading time per week) as well as 3 school-level predictors significantly contributed to reading test scores. However, school-level predictors demonstrated weak predictive ability, which ranged from 0.05 to 0.12.

SuBedi and Howard (2017) explored the relationship between reading achievement and predictors from two both student and teacher levels in elementary, middle, and high schools. HLM results showed that student-level predictors such as race, learning disability, SES, language proficiency, attendance and suspension were statistically significant predictors of reading achievement in all participated schools. At the teacher level, experience in teaching and teachers' effectiveness significantly predicted reading achievement in all the schools and teachers' educational level significantly contributed to reading performance only in middle school and high school. The researchers also detected several significant interaction effects, such as the interaction effect between teachers' effectiveness and suspension in all types of schools.

It is worthy of mention that there were no interaction effects found concerning the particular student-level and school-level predictors included in the current study according to the extensive literature searching results regarding the impacts of student-level and school-level factors on reading achievement. Therefore, the interaction effects were not included or considered as a focus and this resulted in some discussions in school-level model building.

The Development of Hierarchical Linear Modeling

Definition and significance of hierarchical linear modeling. HLM is a sophisticated and versatile statistical methodology for dealing with multilevel data (e.g., students nested within schools, students nested within classrooms) (Snijders & Bosker, 2012). In other words, the prerequisite for using HLM is that data is collected at multiple levels at the same time (Nezlek, 2008). The procedure of sampling of hierarchical data structure disabled the use of linear regression when the prediction problem was considered (Hox, 2002). For example, in the nested data, the sample units of a higher level (e.g., schools) were selected, and then the subsamples from the higher-level unit were drawn (e.g., students). As a result, the particular way of sampling does not allow the individual observations to be completely independent from each other like the independent assumption in linear regression. In other words, the observations at the lowest level (level 1) are dependent because observations share the same resources that the certain organization provides, which leads to common characteristics of observations. Therefore, the similarity of students leads to the average correlation between the dependent and independent variables obtained from students at the same school to be significantly higher than students at different schools. In conclusion, the nature of nested data violates the fundamental independent assumption required by the conventional ordinary least-squares (OLS) approach (e.g., multiple regression). HLM needs to be utilized in the case of predicting the outcome variables in the nested dataset with a set of variables from all variable levels (Hox, 2002).

Two-level model building and descriptions. HLM assumes the hierarchical structure of the dataset, which has one single dependent variable measured at the lowest level and a set of variables from all existing levels. In HLM, the clear annotation of subscripts of each term and their corresponding references in the equation are crucial for understanding because the model can be quite complex with confusing subscripts (Anderson & Brown, 2010; Snijders & Broker, 2012).

Unconditional model. Researchers have developed a practice for starting an unconditional model when considering the application of HLM in the research (Anderson & Brown, 2010). After checking the output of the unconditional model, researchers must make a decision on whether or not to add predictors of interest in each level. A multilevel model contains the submodels that represent its "variation across the lowest level" and "variation across the highest level". For example, the unconditional model (no predictors) equation is listed below as the baseline model of a two-level HLM:

Level 1: $Y_{ij} = \beta_{0j} + r_{ij};$ (1.1)

Level 2: $\beta_{0j} = \gamma_{00} + u_{0j};$ (1.2)

Combined model: $Y_{ij} = \gamma_{00} + u_{0j} + r_{ij}$ (1.3)

In equation 1.1, Y_{ij} is the outcome variable y of ith person in the jth group. According to Sijnders and Bosker (2012), the dependent variable (outcome variable) should occur at level 1 rather than level 2 because HLM handles the cases at the lowest level. β_{0j} is the level-1 intercept in the jth group. In addition, r_{ij} refers to the error for the ith person in the jth group (random effect). In equation 1.2, β_{0j} is set as the dependent variable; γ_{00} is the level-2 intercept which indicates the overall intercept (grand mean) across all groups (fixed effect), and u_{0j} refers to the level-2 error for the intercept in the jth group (random effect). Equation 1.1 can be transformed into the combined model (equation 1.3) by simply substituting the β_{0j} at level 1 with the components γ_{00} and u_{0j} at level 2.

The question of whether HLM is needed should be answered prior to data analysis. This question can be answered by the unconditional model, which calculates how much of the total variance is due to the cluster (Peugh, 2010). An unconditional model with no independent variables is considered as a baseline model and utilized to compute the intraclass correlation (ICC) and design effect statistics. ICC is treated as the estimate which measures the proportion of variation in the outcome variable that occurs between groups and the total variation present, usually ranging from 0 to 1. For instance, an ICC of 0 indicates that all of the variances in the outcome variable occur across students, which further suggests that the traditional regression or ANOVA, which though less complex than HLM is sufficient for the data. In addition to ICC, design effect needs to be considered which was constructed with the known ICC and the number of the clusters of interest in researcher's data.

The equations of ICC and design effect are shown below:

$$\text{ICC} = \rho = \frac{\tau^2}{\tau^2+\sigma^2} \tag{1.4}$$

$$where\ \tau^2 = between\ cluster\ variance, and$$

$$\sigma^2 = within\ cluster\ variance$$

$$\text{Design Effect} = 1+ (\text{n\_cluster}-1)*\text{ICC} \tag{1.5}$$

Building the level-1 model. For multilevel analysis, one or more level-1 predictors can be added to explain its level-specific variation. However, the centering problem which has influence on level-1 model needs to be considered before going further (Peugh, 2010; Raudenbush & Bryk, 2002). Technically, independent variables in social science areas are measured on an interval scale; thus, the value of zero of a predictor variable does not have a significant meaning. Then the question becomes how to avoid the meaningless interpretation of level-1 parameters and make the level-1 predictor variables work properly. Centering procedure enables a predictor variable to rescale so that a value of zero can be regularly understood and expressed in this case (Paccagnella, 2006; Peugh, 2010). The level-1 equation that has the predictors with group-mean centering is demonstrated as following:

$$\text{Level } 1_{\text{(group-mean)}}: \; Y_{ij} = \beta_{0j} + \beta_{1j}\left(X_{1j} - \overline{X}_j\right) + \beta_{2j}\left(K_{1j} - \overline{K_j}\right) + r_{ij} \qquad (1.6)$$

Building the level-2 model. In the same manner, one or more than one predictors can be added into level-2 to explain the level-specific variation. According to Peugh (2010), level-2 predictors are required to be added to level-2 intercept equation only (1.7) if there is no level-1 predictor at all. In addition, the level-2 predictors need to be added to the intercept equation only (1.7) if there is no interaction involved in the research questions as well. Instead, the level-2 predictors are supposed to be added to both intercept and slope equations (1.7, 1.8, 1.9) at the same time if the researchers are interested in the interaction effects.

Researchers must also pay close attention to the additional question of whether the impacts of the predictors at level-1 on the outcome variable should be estimated as a fixed effect only or as a fixed effect with a random effect added. In other words, the question becomes that we do or do not allow the impacts of level-1 predictors on the outcome variable to vary across the groups. According to Peugh (2010), there is no requirement to add random effects to the slope equations if the impacts of the level-1 predictors on the outcome variable stay constant across different groups. The equations are demonstrated as following:

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01} W_{1j} + \gamma_{02} W_{2j} + u_{0j};$ (1.7)

$\beta_{1j} = \gamma_{10};$ (1.8)

$\beta_{2j} = \gamma_{20};$ (1.9)

In equations 1.8 and 1.9, γ_{10} and γ_{20} indicate that the impacts of the level-1 predictors on the outcome variable across each group are not allowed to vary and they are the average effects of the level-1predictors across all groups at the higher level. However, if the impacts of the level-1 predictors on the outcome variable of the individuals vary across the groups, we should estimate those predictors as fixed effects with added random effects in the level-2 slope equations. Thus, the level-2 equations produce:

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01} W_{1j} + \gamma_{02} W_{2j} + u_{0j};$ (1.7)

$\beta_{1j} = \gamma_{10} + u_{1j};$ (1.10)

$\beta_{2j} = \gamma_{20} + u_{2j}.$ (1.11)

In equation 1.10 and 1.11, u_{1j} and u_{2j} are error terms working as the random effects and indicating that the impacts of the level-1 predictors on the outcome variable are allowed to vary across the groups.

CHAPTER III

METHOD

The data used in this study was part of the Progress in International Reading Literacy Study (PIRLS) 2016 international database and data collected in the United States. The International Association of the Evaluation of Education Achievement (IEA) conducts international comparative assessments of fourth-grade students' reading achievement and math performance from more than 60 different countries on a regular five-year cycle. PIRLS collects extensive background information about the reciprocal influence of educational opportunities on students' reading achievement, which includes "student background information, students' home environment for learning, school climates and resources and how instruction actually occurs in classrooms" (Mullis & Martin, 2015, p. 7). Additionally, teachers' experience and knowledge are gathered through questionnaires. Analyzing students' responses to the questionnaires can provide educational policy makers, educators, teachers, and also parents with important insights to help improve reading achievement of students (Foy & Drucker, 2013). In conclusion, the PIRLS data provide a rare yet unique chance for researchers to study possible relationships between student- and school-level predictors and reading achievement at such an important grade level, which can inspire efforts on reading achievement improvement.

Participants

The sample was drawn from the PIRLS 2016 data collection conducted by IEA. Originally, 158 schools including 4,425 fourth-grade students from the United States responded to the questionnaires. In order to obtain student-level and school-level predictors for the current study, data was selected for schools that finished the entire set of questions and for students within those schools who filled out all the student questionnaire items. Therefore, incomplete responses to the questionnaires of students were excluded from selection since they were not useful enough to construct the factors. In addition, incorrectly recorded responses of the questions from students in the dataset were excluded as well. The missing observations of both the student level and school level were deleted listwise, and finally the valid sample size of the data set became 3,001 fourth-grade students nested within 133 schools in the United States. As the data indicate, the ratio of males to females is roughly equal (1,473 males vs. 1,528 females). Among all participants, approximately 18.4% (553 students) are English Language Learners (ELLs). Since more than 30 percent of the original participants were deleted due to incomplete responses to the questionnaires, it is necessary to examine if the deleted participants are not significantly different from the undeleted sample. As a result, one-way ANOVA was conducted to test if there were significant differences between the included group and the excluded group on the overall reading performance. The results indicated that there was a statistically significant difference between these two groups (F (1, 4423) = 67.66, $p < .01$). The reasons for the difference are unknown at this point, which require further studies.

Measurement

Dependent variable. Reading literacy achievement was selected as the dependent variable for the current study. In 1991, IEA defined reading literacy as “the ability to understand and use written language forms required by society and valued by individuals" (Mullis, Kennedy, Martin, & Sainsbury, 2006, p. 3). The definition has been utilized as the core by PIRLS for decades and that is what is expected from young children regarding reading achievement. PIRLS aims to provide high-quality reading assessment to regularly evaluate students' reading accomplishment, such as extracting meaning from text and overall performance in reading (Martin, Mullis, & Foy, 2017).

The PIRLS adopted standardized and step-by-step operation procedures in terms of the consistency and uniformity across all the participating countries. The National Research Coordinators were selected and trained to administrate the PIRLS 2016 assessment (Johansone, 2016). First of all, the administrators got to contact schools to draw sample classrooms for the purpose of assessment administration. Test administrators were assigned to all sampled classes respectively during the assessment administration and they were required to follow the PIRLS test administrator manual to conduct the assessment and student questionnaires.

The number of PIRLS 2016 reading literacy items was relatively large, and it would take more than eight hours for a fourth-grade student to respond to the full battery of tests. Therefore, in order to reduce the burden on test takers, students were not required to finish the entire battery of items (Martin, Mullis, & Foy, 2017). Instead, the total number of items was divided into 12 blocks and the blocks were transferred into 16 booklets (Foy & Lin, 2016). Each of the booklets consisted of two different sections: a literary passage and an informational passage. Students were strictly timed to finish each section in 40 minutes. For example, students were given a 30-minute break between the two sections during the assessment administration, and they were not allowed to leave the testing room until time ran out even though they had finished the test. Some of the items were multiple choice and some were constructed response items. According to Foy, Martin, Mullis, and Yin (2016), the interrater agreement on participant responses to constructed items was .94 and the international median reliability for PIRLS Literacy was .91.

The test administrators distributed the questionnaires to students when the PIRLS assessment was completed. Students needed to finish the questionnaires in 30 minutes. They could request extra time if needed and read aloud the questionnaire items together with the test administrator if they wanted.

Students' literacy achievement was not simply an assigned score in terms of the responses to questions. Rather, their literacy achievement scores were computed based on three components: item responses, estimated item parameters, and student characteristics (Foy & Lin, 2016). According to Foy and Lin, the professional psychometricians of the PIRLS center, conditioning was applied to compensate for the problem that only partial items are given to each student and also for the purpose of increasing the reliability of students' reading scores. Therefore, PIRLS generated five estimates which were known as plausible values for participating students by using the multiple imputation (Rubin, 2011). The plausible values are not traditional achievement scores of students; instead, they indicate the range of possible achievement scores of students (Wu, 2005). The 5 plausible scores of each student were adopted and the mean score of the 5 plausible scores was used as the dependent variable in the model.

Student-level variables. All participating students, teachers, their parents, as well as school principals answered the questions in the questionnaire booklets which are related to their own backgrounds in order to gain a rich array of background information about individual differences among students, home, and school contexts. For instance, students who participated in PIRLS 2016 were administrated a set of questionnaires with questions related to the students' readiness to learn, motivation, their home reading resources, self-concept, and reading literacy behaviors. All variables were derived from the PIRLS 2016 questionnaires to which the participants responded.

English Language Learners (ELL). The students who were involved in the research needed to answer the question "How often do you speak <English> at home" to identify their ELL status. Students filled one of the four responses which best fit their own situations. The responses were coded on a four-point scale (1 = I always speak <English> at home; 2 = I almost always speak <English> at home; 3 = I sometimes speak < English> and sometimes speak another language at home; and 4 = I never speak <English> at home). Students who responded with 3 or 4 were classified as ELLs and those who responded with 1 or 2 were treated as non-ELLs. ELL was dummy coded in order to transform a continuous variable into a dichotomous variable. A dummy value of 0 was adopted to identify the absence of ELL status which referred to the responses of 1 or 2 and a dummy value of 1 represented the presence of ELL status which included the responses of 3 or 4.

Reading motivation. The motivation variable included 21 possible items within two broader categories: reading frequency and reading attitude. Students needed to think about their reading activities and show the extent of their agreement with a set of specific questions. There were 5 items related to the reading frequency included. Two sample items were listed below: "How often do you talk about what you read" and "How often do you read to find out about things you want to learn". It is important to note that the questions were originally coded in an untraditional four-point scale (e.g., 1 = every day or almost every day and 4 = never or almost never). In order to keep the scale conventional, the four-point scale was adjusted (1 = never or almost never; 2 = once or twice a month; 3 = once or twice a week; 4 = every day or almost every day).

In addition, the motivation variable included 16 items of students' reading attitude. A couple of sample items were listed below: "I would be happy if someone gave me a book as a present", "I would like to have more time for reading", "Reading is easy for me" and so forth. The answers were given using a four-point scale. According to the PIRLS website, 4 means disagree a lot, 1 means agree a lot. In order to make the scale conform to the common practice, the scale was reversed in a traditional way (1 = disagree a lot; 2 = disagree a little; 3 = agree a little; 4 = agree a lot). In addition, it is also worth noting that four of the questionnaires on reading attitude asked about students' motivation in a opposite way (e.g., "I think reading is boring", "I have trouble in reading difficult words"). As a result, the responses of these four questionnaires were not reverse coded and the high number (4: disagree a lot) indicated a positive attitude. Therefore, a score of 84 (21*4) indicates the highest level of reading motivation, whereas a score of 21 indicates the lowest level of reading motivation.

Home resources. A home resources variable was created for this study based on students' responses to questionnaires about educational resources at home, for example, "Number of books at home", "Do you have a computer or tablet", "Do you have study desk or table for your use", and "Do you have your own room". The responses of number of books at home were coded in a five-point scale (1= none or very few (0-10 books); 2 = enough to fill one shelf (11-25 books); 3 = enough to fill one bookcase (25-

100 books); 4 = enough to fill two bookcases (100-200 books); and 5 = enough to fill three or more bookcases (more than 200 books)). Further, the responses of learning equipment (table, tablet, internet) were coded in an original two-point scale (1 = yes and 2 = no). In order to keep the scale at the same direction, the responses of learning equipment questions were reversed. Then, the two-point scale becomes that "1" means "no" and "2" means "yes". Thus, the possible value of home resources variable ranges from 5 to 13 and the bigger number indicates higher home resources and vice versa.

School-level variables. In the same way, all the school-level variables were constructed based on the questionnaires completed by the teachers and school principals. The IEA provided teachers and principals with 24-hour availability online questionnaires and each participant received the confidentiality statement and the instruction of how to complete the questionnaires online. The school questionnaire has more abundant information about the potential impacts of school environment.

School SES. According to the school questionnaire booklet, the school SES variable was related to a question which examined the overall economic status of the entire population in each school as well as the questions which asked about the condition of free meals for students of each school. For example, each school answered the question "Approximately what percentage of students in your school come from economically affluent homes", which was coded on a four-point scale (1 = 0 to 10%; 2 = 11% to 25%; 3 = 26% to 50%; 4 = more than 50%). In addition, the schools answered additional questions about free or reduced meals "Does your school provide free breakfast for students" and "Does your school provide free lunch for students". The answers to these two questions were coded into a three-point scale (1 = yes, for all students; 2 = yes, for some students; 3 = no). Thus, the possible value for school SES ranges from 3 to 10 by simply adding the responses, and a higher value indicates higher school SES and a lower value refers to lower school SES.

Teacher's characteristics. The variable of teacher's characteristics was measured by 5 questions. There were 3 example questions listed below: "Teachers' understanding of the school's curricular goals", "Teachers' degree of success in implementing the school's curriculum", and "Teachers' expectations for student achievement". The responses were recorded on a five-point scale (1 = very high; 2 = high; 3 = medium; 4 = low; and 5 = very low). As did for the reading motivation variable, all the responses were code-reversed to present in a tradition al way. The possible variable value of teacher's characteristics ranges from 5 to 25, and a lower value indicates lower level of teacher's characteristics and a higher value indicates higher characteristics of teachers.

School literacy readiness. The school literacy readiness variable was structured based on 6 items which asked about certain types of literacy activities when the students began the first grade of elementary school. For example, "Recognize most of the letters of the alphabet", "Read some words", "Read a story", "Write letters of the alphabet", and "Write some words". There was a corresponding four-point scale with the answers (1 = less than 25%; 2 = 25% to 50%; 3 = 51%-75%; and 4 = more than 75%). The maximum value of the scores is 24 indicating the most optimal readiness and the minimum value is 6 indicating the least literacy readiness.

Grade-level reading proficiency. Finally, the grade-level reading proficiency variable was constructed with 14 questionnaires concerning the specific grade level when reading skills and strategies were emphasized for the first time. The following sample questions were assigned to students in order to detect the school's reading emphasis on a grade-level basis: "Grade level of knowing letters of the alphabet", "Grade level of reading connected text", "Explaining or supporting understanding of a text", "Making predictions about what will happen next in a text", "Making generalizations and drawing inferences based on a text", and "Determining the author's perspective or intention". A five-point scale was provided for the purpose of coding (1 = first grade or earlier; 2 = second grade; 3 = third grade; 4 = fourth grade; and 5 = not in these grade). In the same manner, the reversed codes were utilized in order to make the higher values indicate better reading skills emphasis and vice versa. Therefore, the maximum value of grade-level reading proficiency is 70, indicating the reading skills were emphasized earlier, which is the best situation concerning the time point of reading skills emphasis. On the contrary, the minimum value of 14 indicates that the reading skills were not implemented in a time manner properly.

Procedures

Descriptive statistics. The descriptive statistics of variables was computed as the first step using IBM SPSS version 24. The mean and standard deviations of the entire sample were calculated in terms of each variable at student level and school level. Table 2 demonstrates the descriptive statistics and presents specific interpretations.

Hierarchical linear modeling. One of the main goals of the current study was to examine whether students' reading achievement was associated with student-level factors (ELL, reading motivation, and home resources). Of additional interest was how the school-level predictors (school SES, teacher's characteristics, school literacy readiness, grade-level reading proficiency) were related to students' reading achievement. A two-level HLM was performed by constructing three different models: the unconditional model, the within-school model, and the between-school model. Each model was applied to answer the corresponding research questions in sequence. Given the nested structure of data, R 3.3 was applied to create two-level hierarchical linear models so that we could examine the predictions at varying levels on the fourth-grade students' reading achievement, where student-level factors were included at the first level and school-level factors were included at the second level.

The unconditional model provides an important estimate of the variances within and between schools for the participating fourth-grade students' reading achievement and it is demonstrated as following:

Student level: $Y_{ij(Read)} = \beta_{0j} + r_{ij}$, (2.1)

School level: $\beta_{0j} = \gamma_{00} + u_{0j}$, and (2.2)

Combined Model: $Y_{ij(Read)} = \gamma_{00} + u_{0j} + r_{ij}$, (2.3)

In the unconditional model, the response Y_{ij} is subject to the overall mean across all schools γ_{00}, the variance within school r_{ij}, and as well as the variance between schools u_{0j}. The RQ1 was addressed according to the unconditional model in the analysis to determine whether or not the reading achievement varied among schools.

In order to answer the second and third research questions (RQ2 and RQ3), student-level variables and school-level variables were added into the unconditional model to determine the variations that occurred at both the student and school levels. It is worthy of note that the predictors at the student level were group-mean centered in order to make student-level parameters meaningful (e.g., $ELL_{ij} - \overline{ELL_j}$).

As discussed in the previous chapter with adding the level-1 predictors to the model, we needed to consider the question of whether the impacts of ELL, home resources, and reading motivation on student reading achievement should be treated as fixed effects only or as fixed effects with random effects added. The answer to this question depended on the model comparison with the help of model indices that generated from analyses.

The equations of random intercept and random slope model and random intercept model were all demonstrated as below. For example, the residual terms (e.g., u_{1j}, u_{2j} and u_{3j}) were added as the fixed effects with random effects added and to indicate their changes among schools when the random intercept and random slope model was used (equation 2.6-2.8). In the same manner, the residual terms were not added to the slopes when the random intercept model was adopted (equation 2.10-2.12). In addition, the school-level predictors were only added to the intercept equation because the interaction effects among the predictors across levels were not discussed for the current study. Therefore, the equations for random intercept and random slope model as well as random intercept model were constructed separately.

For example, random intercept and random slope model is shown as below:

Student level: $Y_{ij(Read)} = \beta_{0j} + \beta_{1j}\left(ELL_{ij} - \overline{ELL_j}\right) +$

$$\beta_{2j}\left(homeresources_{ij} - \overline{homeresources_j}\right) +$$

$$\beta_{3j}\left(motivation_{ij} - \overline{motivation_j}\right) + r_{ij}; \qquad (2.4)$$

School level: $\beta_{0j} = \gamma_{00} + \gamma_{01}(schoolSES) + \gamma_{02}(teacher) +$

$$\gamma_{03}(readiness) + \gamma_{04}(proficiency) + u_{0j}; \qquad (2.5)$$

$$\beta_{1j} = \gamma_{10} + u_{1j}; \qquad (2.6)$$

$$\beta_{2j} = \gamma_{20} + u_{2j}; \qquad (2.7)$$

$$\beta_{3j} = \gamma_{30} + u_{3j}. \qquad (2.8)$$

Combined Model: $Y_{ij(Read)} = \gamma_{00} + \gamma_{01}(schoolSES) + \gamma_{02}(teacher) +$

$$\gamma_{03}(readiness) + \gamma_{04}(proficiency) + u_{0j} +$$

$$\left(\gamma_{10} + u_{1j}\right)\left(ELL_{ij} - \overline{ELL_j}\right) + \left(\gamma_{20} +\right.$$

$$\left.u_{2j}\right)\left(homeresources_{ij} - \overline{homeresources_j}\right) +$$

$$\left(\gamma_{30} + u_{3j}\right)\left(motivation_{ij} - \overline{motivation_j}\right) +$$

$$r_{ij}. \qquad (2.9)$$

Random intercept model is shown as below:

Student level: $Y_{ij(Read)} = \beta_{0j} + \beta_{1j}\left(ELL_{ij} - \overline{ELL_j}\right) +$

$\beta_{2j}\left(homeresources_{ij} - \overline{\text{homere}sources_j}\right) +$

$\beta_{3j}\left(motivation_{ij} - \overline{motivation_j}\right) + r_{ij};$ (2.4)

School level: $\beta_{0j} = \gamma_{00} + \gamma_{01}(schoolSES) + \gamma_{02}(teacher) +$

$\gamma_{03}(readiness) + \gamma_{04}(proficiency) + u_{0j};$ (2.5)

$\beta_{1j} = \gamma_{10};$ (2.10)

$\beta_{2j} = \gamma_{20};$ (2.11)

$\beta_{3j} = \gamma_{30}.$ (2.12)

Combined Model: $Y_{ij(Read)} = \gamma_{00} + \gamma_{01}(schoolSES) + \gamma_{02}(teacher) +$

$\gamma_{03}(readiness) + \gamma_{04}(proficiency) + u_{0j} +$

$\gamma_{10}\left(ELL_{ij} - \overline{ELL_j}\right) + \gamma_{20}\left(homeresources_{ij} -\right.$

$\left.\overline{homeresources_j}\right) + \gamma_{30}\left(motivation_{ij} -\right.$

$\left.\overline{motivation_j}\right) + r_{ij}.$ (2.13)

Variation in school-level intercept β_{0j} is predicted by school SES, teacher's characteristics, school literacy readiness, and grade-level reading proficiency within the jth school. The combined model was utilized for the purpose of further data analysis as required by the software and to answer three research questions proposed in the introduction. In addition to the research questions of the current study, another crucial focus was to apply and generalize the findings into further studies and real educational activities. In accordance with pre-existing studies, this multilevel analysis may stimulate some new ideas about the variables at different levels that have influence on students' reading achievement.

CHAPTER IV

RESULTS

Descriptive statistics

Table 1 summarizes the descriptive statistics regarding the sample size, means and standard deviations of all the variables. The overall reading scores ranged from 255.15 to 745.57 with the mean of 554.74 and standard deviation of 72.78. In addition, the results of skewness and kurtosis indicated that reading achievement scores presented a normal distribution (skewness = -.43 and kurtosis = -.013).

The result showed that more non-ELL students were involved as the participants as indicated by the mode of 0 (2,448 non-ELLs vs. 553 ELLs). Home resources examined students' reading resources at home by answering 5 questions (the possible value ranged from 5 to 13) about their educational resources at home (e.g., "Number of books at home" and "Do you have a computer or tablet"); the larger number indicated more abundant home reading resources. For example, the mean of 10.52 showed that the participants had relatively rich reading resources at home on average. Similarly, reading motivation examined students' reading interest according to 21 motivation-related items (e.g., "I would like to have more time for reading", "I would be happy if someone gave me a book as present") and the higher scores indicated higher reading motivation. The results showed that students demonstrated passions and positive attitude on reading on average (M = 64.96, SD = 10.52; the possible score ranged from 21-84), but the conditions of reading motivation of students spread out in terms of a wider range of values (e.g., relatively large standard deviation).

At the school level, school SES measured the economic status of the school by answering 3 questions of free breakfast/lunch and the percentage of the students who come from the economically affluent homes and higher value indicated higher school SES. The possible value for school SES variable ranged from 3-10 (see the Method section for detailed descriptions of the variable scale) and the results (M = 5.33, SD = 1.7) indicated that the schools were at a moderate economic status on the average. The teacher's characteristics variable focused on teacher's understanding and success of reading instruction (e.g., "Teachers' understanding of the school's curricular goals" and "Teachers' collaboration to plan reading instruction") and the mean of 15.13 indicated that teachers were showing high standard in delivering reading instructions on average as the possible value for the variable of teacher's characteristics ranged from 5 to 25. The mean of school literacy readiness was 18.92 with the standard deviation of 5.92 and grade-level reading proficiency obtained the mean of 62.92 points with the standard deviation of 6.16. Combining the possible values of school literacy readiness (6-24) and grade-level reading proficiency (14-70), it showed evidence that students gained sufficient reading readiness and proficiency on the average.

Table 1
Descriptive Statistics for Key Variables (N = 3,001)

	M	*SD*	Min	Max	Range
Overall Reading	554.74	72.78	255.15	745.57	490.42
ELL	0.18	0.39	0	1	1
Home Resources	10.15	1.57	5	13	8
Reading Motivation	64.96	10.52	26	84	58
School SES	5.33	1.7	3	9	6
Teacher's Characteristics	15.13	3.05	6	20	14
School Literacy Readiness	18.98	5.92	6	24	18
Grade-level Reading Proficiency	62.92	6.16	36	70	34

Correlation

The correlations between key variables are presented in Table 2. ELL status was found to be negatively correlated with home resources (r = -.169, p < .01) and school SES (r = -.168, p <.01). In other words, non-ELLs (coded as 0) possessed better home resources and attended higher-SES schools than ELLs (coded as 1). Furthermore, ELL status was found to be relatively independent from reading motivation, teacher's characteristics, school literacy readiness, and grade-level reading proficiency. The variable of home resources was positively related to all the predictors from both the student and school levels with the largest magnitude between school SES and home resources (r = .303, p < .01). Reading motivation was not found to be significantly correlated to school-level predictors except a marginal correlation with grade-level reading emphasis ($r = .065$, $p < .01$). In addition, school SES was correlated to all school-level predictors and the strongest correlation between school SES and school literacy readiness ($r = .376$, $p < .01$) was detected, indicating that the higher school SES, the higher school literacy readiness that students obtained. The correlation results also indicated that teacher's characteristics and grade-level reading emphasis were relatively independent from the other variables. School literacy readiness was not related to the other predictors except its correlation with school SES ($r = .376$, $p < .01$) and its weak correlation with teacher's characteristics ($r = .052$, $p < .01$).

Table 2
Correlation Matrix for Key Variables

	ELL	Home Resources	Reading Motivation	School SES	Teacher's Characteristics	School Literacy Readiness
ELL						
Home Resources	-.169**					
Reading Motivation	-.017	.209**				
School SES	-.168**	.303**	-.015			
Teacher's Characteristics	-.038*	.075**	.025	.156**		
School Literacy Readiness	-.024	.161**	-.033	.376**	.052**	
Grade-level Reading Proficiency	-.020	.074**	.065**	.122**	.043*	-.028

**. Correlation is significant at the .01 level (2-tailed).
*. Correlation is significant at the .05 level (2-tailed).

Hierarchical Linear Modeling Analyses Results

A series of hierarchical linear models were applied to examine the effects of the predictors from the student and school levels on reading achievement of the fourth-grade students to address the respective research questions. Note that the restricted maximum-likelihood (REML) estimation method was used assuming the estimation was performed as sample statistics.

Unconditional model (M_0). The unconditional model was first built to estimate the within- and between-school variances to respond to the first research question. There was no explanatory variable involved in the unconditional mode; however, it still conveyed important information in terms of the data structure. In addition, the unconditional model plays the role as a baseline in the model comparison, which is a necessary procedure in HLM.

The intraclass correlation of the unconditional model (ICC = .25) along with the design effect (DE = 6.33) provided statistical support for the adoption of HLM, suggesting that 25% of the variance in reading achievement scores of the fourth-grade students were explained at the school level. In other words, 75% of the variance in reading achievement was due to student-level effects within schools. The DE value of 6.33 exceeded the criterion value of 2.00 for the need of HLM analysis. Similarly, the estimates of covariance parameters for student level (σ^2 = 3979.27, p <. 05) and school level (σ^2 = 1306.13, p < .05) indicated that there was significant variation at both the student and school levels that could be explained. As a result, additional student-level and school-level predictors to explain the variation were added.

Student-level model (M_1). To answer the second research question, the conditional models with student-level predictors were generated through both random intercept model and random intercept and random slope model simultaneously. As it was proposed, model comparison directs to pick the most appropriate model among different available options.

Model comparison of HLM is a standard procedure in order to obtain the best fitting model by testing if there is a significant difference between the overall fit of the two models (Finch, Bolin, & Kelley, 2019). Goodness-of-fit indices including Akaike Information Criterion statistic (AIC), Bayesian Information Criterion statistic (BIC) and $\chi2$- test statistic were used for generating several pairs of model comparisons in this study (e.g., random intercept model vs. random intercept and random slope model, M_0 vs. M_1, M_0 vs. M_2, and M_1 vs. M_2).

It has been proposed by Dziak, Coffman, Lanza, Li and Jermiin (2019) that “AIC estimates the relative Kullback-Leibler (KL) distance (a nonparametric distance measure) of the likelihood function specified by a fitted candidate model, from the unknown true likelihood function that generated the data” (p. 3). In addition, “In Bayesian model selection, a prior probability is set for each model…BIC is an estimate if we assume that one and only one model is true” (p. 4). As a result, lower numbers of AIC and BIC indicate that the model is closer to the data; namely smaller AICs and BICs refer to better model fit (Finch, Bolin, & Kelley, 2019). Dziak and his co-authors further revealed that BIC is more preferable than AIC because of its consistency. In addition, it makes little sense if the comparison difference between two models in terms of AICs is less than 2. As a result, model comparison requires the difference between AICs to be at least 10. Meanwhile, a likelihood ratio test (the difference between two deviance statistics) can be used to test the model fit by referring to a $\chi2$- test distribution with certain degrees of freedom, which is equal to the difference between the number of estimated parameters for each model (Anderson, 2012; Peugh, 2010).

The model comparison results indicated that there were no significant differences between random intercept models and random intercept and random slope models at the student level according to the $\chi 2$-difference test ($\chi 2$ (3) = 33317-33315 = 2, $p > .05$) even though the former model yielded smaller AIC and BIC statistics. However, the principle of parsimony suggests that models should contain as few parameters as possible in order to meet the law of simplest is the best. Therefore, the random intercept model, which performed as the less complex model was eventually adopted at the student level (Vandekerckhove, Matzke, & Wagenmakers, 2015). The proposed random intercept model allowed the intercept of reading achievement scores of each school to vary and the slopes were treated as fixed effects across schools.

Fixed effects of student-level predictors were regarded as the regression coefficient in the interpretation. For example, a fixed effect of ELL ($\hat{\gamma}_{10} =$ -10.82, $p < .01$) meant that there was a significant difference between reading achievement scores of ELLs and non-ELLs. On average, ELLs achieved 10.82 points lower than non-ELLs on reading scores when controlling for the home resources and reading motivation; the fixed effect of home resources ($\hat{\gamma}_{20} =$ 7.04, $p < .01$) indicated that as students' home resources score increased by 1 point, their reading achievement score increased by 7.04 points; and the fixed effect of reading motivation ($\hat{\gamma}_{30} =$ 1.56, $p < .01$) indicated that as students' reading motivation increased by 1 point, their reading achievement scores increased by 1.56 points. The fixed intercept of 549.71 was the mean of reading achievement score when the values of students' ELL, home resources and reading motivation were all 0 (Table 3). In short, the ELL status of student, variations in home resources, and different degrees of reading motivation all significantly predicted reading achievement scores at the student level (Table 3).

Table 3
HLM Model Summaries

Parameters	Unconditional model(M_0)	Student-level model (M_1)	Full model (M_2)
regression coefficients (fixed effect)			
Intercept ($\hat{\gamma}_{00}$)	549.81**	549.71	402.69**
ELL ($\hat{\gamma}_{10}$)		-10.82**	-10.82**
Home Resources ($\hat{\gamma}_{20}$)		7.05**	7.05**
Reading Motivation ($\hat{\gamma}_{30}$)		1.56**	1.56**
School SES ($\hat{\gamma}_{01}$)			13.93**
Teacher's characteristics ($\hat{\gamma}_{02}$)			0.60
School Literacy Readiness ($\hat{\gamma}_{03}$)			0.71
Grade-level Reading Proficiency($\hat{\gamma}_{04}$)			0.85*
Variance components (random effects)			
Residual ($\hat{\sigma}^2$)	3979.27**	3540.95**	3541.49**
Intercept ($\hat{\tau}^2$)	1306.13**	1329.21**	635.05**
Model summary			
AIC statistic	33661	33321	33232
BIC statistic	33673	33333	33244
Deviance statistic	33657	33317	33228
Number of estimated parameters	3	6	10

* p <.05
**p <.01

In addition to the estimates of the fixed effects, it is also necessary to report the effect size of HLM to assess how the model is performing. Recchia (2010) proposed that the classical concept of R^2 from multiple regression analysis cannot be adopted by HLM directly because the variance in the outcome variable is partitioned into level-1 and level-2 components. Fortunately, a proportional reduction in variance (*PRV*) index can be calculated to estimate the amount of variance in the response variable by comparing the variance in the model prior to adding explanatory variables to the variance in the model that contains the additional explanatory variables. Thus, in terms of the estimates of covariance parameters, the results of $PRV\ (\frac{\sigma^2_{M0}-\sigma^2_{M1}}{\sigma^2_{M0}} = \frac{3979.27-3540.95}{3979.27} = .11)$ indicated that the inclusion of student-level predictors reduced the error variance of reading achievement at the student level by approximately 11%. In other words, about 11% of student-level variance was explained by students' ELL, home resources and reading motivation and the majority of the variance (89%) remained unexplained since other explanatory variables were not included at the student level to account for the remaining variance. Additionally, it should be noted that 75% of the variance in reading achievement was due to the within-in school effects (ICC = .25). As a result, student-level predictors explained about 8.3% (11%*75%) of the total variance in reading achievement. Even though student-level predictors were added, there were still significant variations that could be explained at both the student and school levels. As random intercept model was adopted, the variance at the school level became the variations in the intercepts of students' reading achievement scores across schools. Therefore, it led student-level model to incorporate additional school-level predictors to account for the variations in the intercepts.

Model comparison was done between the unconditional model (M_0) and student-level model (M_1) in order to see the model improvement by adding student-level predictors. The results of model comparison indicated that the AIC and BIC statistics were 33661 and 33673 for M_0 and 33321 and 33333 for M_1 respectively. In addition, the difference in the deviance statistics between M_0 and M_1 ($deviance_{M0}$-$deviance_{M1}$ = 33657-33317 = 340) showed that predicting students' reading achievement with student-level predictors was significantly better than the unconditional model without predictors ($\chi2$ (3) = 340, $p < .01$). In conclusion, there was a significant increase in the model fit as a result of adding student-level predictors into the model.

Full model (M_2). As discussed earlier in the discussion of student-level models, a random intercept model with student-level predictors was selected to perform in the analysis. Therefore, additional school-level predictors including school SES, teacher's characteristics, school literacy readiness and grade-level reading proficiency were added to the current random intercept model and produced the full model (M_2) to account for the variation in the intercepts.

The estimated intercept of 402.69 indicated the average reading score for a student who had an average overall school SES, average overall teacher characteristics at school, overall school literacy readiness and overall grade-level reading proficiency of the entire sample. The estimated slope of school SES ($\hat{\gamma}_{01}$ = 13.93, $p < .01$) meant that as school SES increased by 1 point, reading achievement score increased by 13.93 points. The results indicated that teacher's characteristics did not demonstrate a statistically significant relationship with reading achievement of students ($\hat{\gamma}_{02}$ = 0.60, t = .74, $p > .05$). In the same manner, school literacy readiness of students was not a significant predictor of students' reading achievement at the student level ($\hat{\gamma}_{03}$ = 0.71, t = 1.61, $p > .05$). The estimated fixed effect of grade-level reading proficiency ($\hat{\gamma}_{04}$ = .85, p

< .05) indicated that as students' grade-level reading proficiency improved by 1 point, students reading achievement score increased by .85 point. Considering the scale of reading achievement scores (M = 554.74, SD = 72.78) in this study, the impact of grade-level reading proficiency can be ignored since the magnitude of score increase is relatively small.

The proportional variance reduction (PRV) in school-level intercept variance that resulted from the addition of student-level predictors can be obtained by subtracting the intercept variance estimate of the full model (M_2) from the intercept variance of student-level model (M_1). The different value of the intercept variance was divided by the student-level intercept variance ($PRV = \frac{\tau^2_{M1} - \tau^2_{M2}}{\tau^2_{M1}} = \frac{1329.21 - 635.05}{1329.21} = .52$). The value of PRV (.52) indicated that by introducing the school-level predictors into the model, 52% of the variance in the intercept of reading achievement was explained at the school level. In other words, the unexplained variance in intercept decreased by 52% after adding school-level predictors. However, about 48% of the variance in the intercept in reading achievement remained unexplained because the factors that may explain the variance were not included in the model at the school level. Therefore, the unexplained variances allowed the current model to theoretically identify other predictors that would help to explain variation in the intercepts. In addition, the value of ICC (.25) indicated that 25% of the variance in reading achievement was between schools so that school-level predictor (school SES) explained approximately 13% (52%*25%) of the total variance in reading achievement scores. Provided the significance of fixed effects and proportional reduction in variance, the varying intercepts (different average reading achievement scores across schools) between different schools can be explained by school SES for 52% and the inclusion of school-level predictors explained 13% of the total variance in reading achievement.

There were two additional pairs of model comparisons conducted and the results indicated that the full model (M_2) which included both student-level and school-level predictors significantly improved the model fit compared to M_0 ($deviance_{M0}$-$deviance_{M2}$ = 33657-33228 = 429; $\chi 2$ (7) = 429, $p < .01$) and M_1 ($deviance_{M1}$-$deviance_{M2}$ = 33317-33228 = 89; $\chi 2$ (4) = 89, $p < .01$, Table 3). The smallest values of AIC and BIC of M_2 (33232 and 33244) were consistent with the $\chi 2$- test results by indicating best model fit of the full model.

CHAPTER V

DISSCUSSION

As is indicated by the literature review, it is crucial to investigate the impacts of any possible factors on reading achievement due to the concerns of reading performance in the U.S. NAEP reported the latest decrease in average reading achievement score of the fourth-grade students in 2019, which reminds us of the necessity for further and deeper efforts to improve students' reading achievement. Although the research on the predictors from the student and school levels is abundant, research involving factors from both the student and school levels simultaneously is still in high demands. The present study sought to explore how student- and school-level factors predict reading achievement of the fourth-grade students simultaneously and how they perform in their predictions. HLM helped identify variation in reading achievement among students across different schools and observed the specific impacts of student-level and school-level factors on reading achievement. As a result, the discussion chapter reviewed this research study and statistical findings, addresses the educational implications, explains limitations, and identifies sites for further.

Overview

First of all, the descriptive statistics results indicated that the majority of the participants were native English speakers and most of them obtained rich home reading resources. However, the descriptive statistics of reading motivation indicated that some of the students demonstrated extremely high reading motivation whereas some of them showed litter interest in reading even though their mean reading motivation score was relatively high. This is consistent with the reality that the efforts of creating motivation and engagement to learn reading have been invested for decades due to the individual differences in terms of their reading passions (Guthrie, Wigfield, Humenick, Perencevich, Taboada, & Barbosa, 2006; Pintrich, 2003). The school-level predictors indicated that the participated schools possessed moderate school SES, teachers at those schools were equipped with good understanding of reading instruction, and students obtained sufficient reading readiness and proficiency from the schools they attended.

The correlation matrix indicated that the variables at both the student and school levels remained relatively independent from each other except the strongest correlation between school SES and school literacy readiness. It is informative to examine the correlation matrix of all variables involved because multiple factors at each level were included. As a result, it is desirable to keep each of the variables not to be highly correlated with each other in order to avoid the multicollinearity issues in the analysis. For example, at the school level, school literacy readiness and grade-level reading proficiency factors were constructed using similar questionnaires regarding students' reading skills. Thus, involving these two in the analysis at the same time may be redundant. However, the results showed that school literacy readiness was not related to grade-level reading proficiency at all, indicating that including both of them as predictors at the school level was reasonable.

Having the opportunity to explore reading achievement from more than one level contributes to a more comprehensive understanding of reading achievement. Therefore, the present study utilized an advanced statistical technique, HLM, to a large-scale public data set to explore the impacts of student- and school-level factors on reading achievement. The unconditional model was first generated to answer the first research question and to examine the necessity of HLM over traditional regression analysis prior to performing the analyses. The ICC and DE results confirmed that there was proportional variance (25%) in reading achievement due to the schools, which inspired this study's inclusion of both student-level and school-level factors into the models to explain those variations among schools in addition to the variance at the student level (75%). The findings provide statistical support for applying HLM into data analysis rather than multiple regression as well as for including student-level and school-level factors since there were variations in reading achievement across schools observed.

A student-level model with predictors was built in order to respond to the second research question. Results indicated that ELL status, students' home resources and reading motivation were all significantly correlated to the fourth-grade students' reading achievement with varying levels. The ELL status demonstrated the highest predictive capacity, followed by home resources, and reading motivation came last. In terms of ELL status, there were significant differences between ELL group and non-ELL group with non-ELLs achieving 10.82 points higher than ELLs on the reading achievement scores. The findings are consistent with Abedi (2002), which showed that ELLs achieved lower than non-ELLs on reading, science, and math, whereas the largest performance gap occurred between ELLs and non-ELLs in reading assessment. In addition, home resources significantly predicted reading achievement scores of students at the student level by showing that better home learning resources produced higher reading achievement scores. However, reading motivation did not perform as well as the other two student-level factors in the prediction as determined by the relatively small fixed effect ($\hat{\gamma}_{30} = 1.56$) of home resources. The results further indicated that student-level predictors (ELL, home resources and reading motivation) explained about 11% out of 75% of the variance at the student level. In other words, student-level predictors accounted for 8.3% of the total variance in reading achievement. In addition, the second research question was supported because student-level model with explanatory factors was significantly better than the unconditional model through the $\chi 2$- difference test results.

Continuing to expand the unconditional model and to respond to the third research question, school-level predictors (school SES, teacher's characteristics, school literacy readiness, and grade-level reading proficiency) were added into the model to explore how they would perform in explaining the varying intercept of reading achievement among different schools. The results indicated that only school SES and grade-level reading proficiency were significant predictors of reading achievement with teacher's characteristics and school literacy readiness not being significantly correlated to reading achievement. Given the magnitude of the fixed effect of school SES ($\hat{\gamma}_{01} = 13.93$), school SES played an important and dominant role in predicting reading achievement scores of the fourth-grade students. However, grade-level reading proficiency yielded weak predictive capacity which was basically negligible. The findings revealed that there was a marginal between-school variance (25%) compared to within-school variance (75%) in reading achievement. The results further showed that the inclusion of school-level predictors explained about 52% out of 25% of the variance at the school level. In other words, school-level factors accounted for approximately 13% of the total variance in reading achievement and the variance was mainly explained by school SES. Furthermore, there was a significant improvement on the full model compared to the unconditional model and student-level model, which proved the significance and necessity of adding school-level predictors into the model. Therefore, the most complicated full model turned out to be the best model for the complex phenomena which would predict reading achievement at more than one level.

Combining student-level and school-level results, these findings reach the conclusion that the nature of reading is an extremely complex concept. For instance, the predictions from two levels together did not explain the variance in the outcome variable of reading achievement optimally even though the models proportionally reduced some variances. The student-level along with school-level variables explained approximately 21% of the total variance in reading achievement of the fourth-grade students in the PIRLS 2016 data. In other words, the selected student-level factors as well as school-level factors were not adequate enough to explain individual differences and the variations in the intercepts among schools in reading achievement. Nevertheless, it still provided valuable information to researchers when reading achievement was explored.

Limitations and Recommendations for Future Study

No research is perfect and we may expect some limitations from the current project. The PIRLS data contain the plausible values for students' reading achievement scores. The plausible values are not real test scores of individuals. According to Monseur and Adams (2009), "plausible values are random numbers that are drawn from the distribution of scores that could be reasonably assigned to each individual…plausible values contain random error variance components and are not optimal as scores for individuals" (p. 6). It has been suggested that the analysis should be generated five times accordingly, and then the obtained five-time results should be averaged when the plausible values were used in order to reach the ideal condition. For the current project, I only averaged the five plausible scores that PIRLS provided following other similar studies (Damme, Liu, Vanhee, & Pustjens, 2010; Grilli, Pennoni, Rampichini, & Romeo, 2016). Thus, we encourage researchers who are interested in the plausible values to generate analyses according to the suggested procedure so they could observe the merit of plausible values.

The second limitation of the current study is that the variance in reading achievement was only partially explained at the student level and a large portion of the variance remained unexplained. The findings indicated that student-level factors—ELL, home resources, and reading motivation—were not exhaustive enough to account for all the individual differences in reading achievement. Clearly, there are other factors influencing reading achievement that are not included in this study at the student level. Thus, it should be noted that other factors need to be considered and examined in order to have a fuller understanding of the individual differences in reading achievement.

The third limitation of the current study is that we selected a limited number of school-level variables due to multiple available variables in the large-scale data set. However, they did not reach the desirable results as expected. For example, at the school level, only school SES and grade-level reading proficiency significantly predicted reading achievement of students with limited predictive capacity of the later predictor. In other words, the school SES alone was dominating the prediction among all four predictors. Therefore, this leaves enough room for further studies to explore more valuable predictors to include in their own research if examining reading achievement through HLM draws their interest. Moreover, seeking help from statistical techniques as this study does to generate variables effectively from a large-scale data set is strongly recommended (e.g., Lasso regression) (Fonti & Belitser, 2017).

Furthermore, this study suggests that researchers should take classroom level into consideration in addition to the student and school levels, as it may produce more informative results. Adding additional level in the analysis increases the complexity yet covers more aspects so that reading achievement can be understood better. Since not all factors having impacts on reading achievement were introduced in the current study at both the student and school levels, we suggest involving additional predictors at both levels. For example, parental involvement in home reading activities (Gilleece, 2015) and self-confidence (Ghaith, 2003) can be included at the student level and teachers' support (Jensen, Solheim, & Idsøe, 2019) and class size (Chatterji, 2006) can be obtained at the school level.

Regardless of the limitations, this study yielded several educational insights by showing that the factors from the student and school levels have significant impacts on reading achievement of the fourth-grade students. The results showed that non-ELLs generally outperformed ELLs on reading achievement, which implied that researchers, educational experts, and school educators need to work harder to narrow the gap between ELL students and non-ELL students since it is a significant obstacle to reading development. Individual differences between ELLs and non-ELLs guide various instructions and the learning outcomes of students. As a result, efforts to narrow the gaps between ELLs and non-ELLs lead to the consideration of specific instructional services for students who have unique demand in order to reduce the negative impact of language proficiency on other subjects and assessment performance. It is also evident that home resources play an important role in predicting reading achievement. Therefore, parents who are not aware of the influence of home reading resources on reading achievement should make some changes to guarantee students' reading exposure at home. The strong impacts of reading motivation imply that encouraging students to develop the habit of reading requires the joint efforts of teachers, students and parents at the same time. For example, teachers can create a vibrant atmosphere for reading class to motivate students to enjoy reading, parents can encourage students to read to explore the unknown world and students need to learn the importance of reading and experience the joy of reading.

Last but not the least, the results showed that school SES significantly predicted reading achievement at the school level and explained a large amount of variance in the intercept of reading achievement scores of schools. However, there is very little we can do as teachers and researchers to increase the socioeconomic status of schools. What we can do is take the school SES into consideration when the discussion on reading achievement is introduced.

In the past, research only focused on the impacts of individual characteristics or school-level effects on reading achievement, with few of them targeting different levels at the same time. Thus, this study may serve as a reminder that reading is a multidimensional concept and improving reading achievement is a long-term process which requires determined efforts from a variety of parties. Exploring from different levels rather than a single dimension may broaden our understanding and arouse new ways of assessment when reading achievement is investigated. As this study reveals, the most effective way of improving reading achievement is to take the combined attempts and efforts of students themselves, teachers, parents, and schools as they all have positive impacts on reading achievement. Any attempts and efforts cannot be ignored because they are the small pieces of the huge puzzle of reading achievement which eventually lead us to be closer to the destination of totally understanding the individual differences of students in reading achievement.

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