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Ecological Dynamics of Reading Performance: A Structural Equation Model with PIRLS 2021 Türkiye Data

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Reading performance in the primary grades is shaped not only by students' cognitive skills but also by the personal, school, and family conditions in which literacy develops. Understanding these multilayered influences is particularly important for Türkiye, where PIRLS 2021 offers a nationally representative opportunity to examine fourth-grade reading achievement after a two-decade interval in participation. Guided by Zumbo's ecological framework, this study investigated the direct and interrelated effects of reading self-efficacy, students' attitudes toward school, and parents' attitudes toward their children's school on reading performance. The sample comprised 6,032 fourth-grade students in Türkiye, together with corresponding parent and school administrator data from PIRLS 2021. Missing data were addressed through multiple imputation, and construct validity was examined through confirmatory factor analysis before estimating the final structural equation model. The model demonstrated good fit. Reading self-efficacy showed the strongest positive effect on reading performance, followed by students' attitudes toward school and parental attitudes. Covariance estimates indicated a moderate association between reading self-efficacy and school attitudes, whereas parental attitudes were only weakly related to students' self-perceptions. These findings suggest that the personal characteristics layer has greater explanatory power than the school and family layers, while still operating within a broader ecological structure. The results highlight the need to strengthen students' reading self-beliefs, foster supportive school climates, and improve home–school partnerships. Future research may extend the model by incorporating additional ecological layers and testing longitudinal or multilevel pathways.

Introduction

Reading achievement, as a core component of literacy, underpins academic success and long-term educational attainment (Carr, 2024; Karatay, 2023). Early reading proficiency, in particular, has been shown to predict students' future academic engagement and self-

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concept (Taylor et al., 2020). Accordingly, improving reading performance remains a central educational priority in Türkiye and beyond (MEB, 2024). These policy shifts reflect growing recognition that reading is shaped by developmental, social, and environmental conditions (Chen et al., 2021; Göktentürk, 2021). Nonetheless, despite these policy-level commitments, the mechanisms through which such diverse influences operate remain underexplored.

A key limitation in the existing literature is the tendency to examine student-, school-, or family-related factors in isolation. While many studies have explored individual predictors such as motivation (Oruç et al., 2024) or socio-economic background (Suna & Özer, 2021), these analyses often fail to consider the broader context in which students learn. For example, a child's reading competence may be shaped not only by personal characteristics but also by the perceptions of school environment and the level of parental engagement (Gay et al., 2021; Tegmark et al., 2022). Understanding reading achievement as the product of these overlapping domains necessitates an integrated approach.

Rather than treating these factors independently, Zumbo's ecologically grounded framework offers a promising roadmap for examining how personal, school, and family layers interact to shape student outcomes (Göktentürk et al., 2023; Sağlam et al., 2023). Although not developed specifically for academic achievement, the model situates educational variables within broader ecological contexts and supports an integrated understanding of learning processes (Zumbo et al., 2015; Zumbo, 2017). This perspective is particularly relevant for fourth-grade students, who are at a developmental stage where foundational reading skills consolidate and external influences—such as school climate and family involvement—begin to exert more sustained effects (Gilavand, 2016). Examining these domains together provides a comprehensive view of the ecological conditions shaping reading achievement.

The 2021 cycle of the Progress in International Reading Literacy Study (PIRLS) offers a unique opportunity to examine these dynamics. Türkiye's re-entry into PIRLS after two decades provides nationally representative data capturing diverse contextual influences on reading (IEA, 2024a). The richness of this dataset enables the analysis of interrelated influences on reading achievement and supports the development of models that reflect the complexity of students' learning environments (IEA, 2023a). In light of these considerations, the present study seeks to investigate the ecological dynamics of reading achievement among fourth-grade students in Türkiye. Specifically, it addresses the following research questions:

(1) What is the best-fitting model that explains the ecological background of reading achievement among fourth-grade students in Türkiye?

(1.1) To what extent does reading self-efficacy, as a factor within the person characteristics layer, account for variation in students' reading achievement?

(1.2.) To what extent does students' attitude toward school, as a factor within the school layer, explain their reading achievement?

(1.3.) To what extent does parents' attitudes toward children's school, as a factor within the school layer, explain students' reading achievement?

Theoretical Framework and Literature Review

Reading Self-Efficacy and Reading Performance

Reading self-efficacy a student's belief in their capacity to succeed in reading tasks is a key personal factor that shapes engagement, motivation, and persistence during literacy activities (Bandura, 2012; Chen et al., 2021). Students who perceive themselves as competent readers are more likely to approach texts with confidence, sustain effort in the face of difficulty, and develop positive academic dispositions (Ortlieb & Schatz, 2020). As such, reading self-efficacy supports not only performance but also the development of lifelong literacy habits.

Empirical studies consistently show that students with higher self-efficacy achieve better reading outcomes, particularly in comprehension, and demonstrate greater motivation and perseverance in literacy tasks (Nutton, 2020; Unrau et al., 2018). These associations are especially salient in primary education, where students' self-perceptions begin to solidify through classroom feedback and experience. In Türkiye, PIRLS data from 2001 and 2021 show parallel gains in students' reported self-efficacy and reading achievement (Mullis et al., 2023; Mullis et al., 2003). While a direct causal relationship is not specified, this alignment suggests that growing student confidence may have contributed to improved reading outcomes. Accordingly, reading self-efficacy is positioned in this study as a critical personal variable that may help explain variation in reading performance within an ecological model.

Reading self-efficacy also reflects broader interactions with the learning environment, including teacher support, classroom experiences, and home literacy practices (Chen et al., 2021). Within Zumbo's ecological framework, it represents the innermost layer of personal characteristics, embedded in and shaped by wider contextual influences (Göktentürk et al., 2023; Zumbo et al., 2015). Given its centrality to both personal development and academic achievement, the study tests the following hypothesis:

H_1: Reading self-efficacy predicts reading performance.

Attitudes Toward School and Reading Performance

Students' attitudes toward school—encompassing their sense of belonging, emotional safety, and perceived support—shape how they experience and engage with the learning environment (Longobardi et al., 2021). Positive attitudes have been shown to enhance academic motivation and behavior, including greater interest and effort in reading tasks (Cain & Hattie, 2020; Lai et al., 2015). This connection is particularly pronounced in primary education, where students are highly sensitive to external cues (Cayubit, 2022). At this stage, emotional experiences within the classroom can significantly influence academic performance (Ma et al., 2021). When students feel valued and supported, they are more likely to approach reading with confidence and persistence, thereby strengthening literacy development (Erwin et al., 2024; Gilavand, 2016).

The influence of school attitudes is better understood when situated within a broader ecological context. Rather than functioning independently, students' perceptions of school interact with personal and familial characteristics to shape educational outcomes (Bogunović & Polovina, 2007; Huang & Anyon, 2020). Within Zumbo's ecological framework, attitudes toward school are located in the school context layer and may serve as a conduit through which environmental quality impacts learning behaviors (Göktentürk et al., 2023; Zumbo et

al., 2015). This positioning allows for a more integrated understanding of how emotional connection to school contributes to reading achievement. Based on this literature and its ecological framing, the following hypothesis is proposed:

H_2: Students' attitudes toward school predict reading performance.

Parents' Attitudes Toward Children's School and Reading Performance

Parents' attitudes toward their child's school—encompassing trust in teachers, communication openness, and perceived academic support—shape both their engagement with school and the learning environment at home (Räty & Kasanen, 2007). When parents hold positive views of the school, they are more likely to stay in contact with teachers, participate in school activities, and reinforce academic values at home, thereby supporting reading development (Yang et al., 2023). Although parental involvement may not exert as immediate an influence as classroom-level factors, research suggests that parents' school attitudes impact reading outcomes through indirect pathways (Ball et al., 2021). Positive perceptions can encourage structured home learning environments and model supportive reading behaviours, both of which contribute to students' literacy over time (Soyoof et al., 2024). Thus, even indirect parental engagement becomes a valuable component of the learning ecology.

Within Zumbo's ecological framework, parental attitudes belong to the outer, family-related layer. Although more distal than classroom factors, they contribute meaningfully to students' academic development by shaping the context in which learning occurs (Göktentürk et al., 2023). When viewed ecologically, home–school alignment and parental support emerge as critical contextual resources for reading success. In line with this literature and its theoretical framing, the following hypothesis is proposed:

H_3: Parents' attitudes toward their child's school predict reading performance.

Zumbo's Ecological Framework in the Context of PIRLS 2021

Zumbo's ecological model conceptualizes educational performance as the result of interactions across multiple, interconnected layers—ranging from individual characteristics to school and family environments (Saglam & Goktenturk, 2024; Zumbo, 2017). Rather than isolating variables, the model emphasizes how dynamic, *in vivo* interactions among personal, social, and institutional factors jointly shape learning outcomes (Göktentürk et al., 2023; Zumbo et al., 2015). In this framework, educational achievement is not solely the product of cognitive ability but emerges from learners' ecological backgrounds (Göktentürk et al., 2023). Accordingly, this study adopts a layered approach to investigate how personal, school, and family factors combine to influence reading performance (see Figure 1).

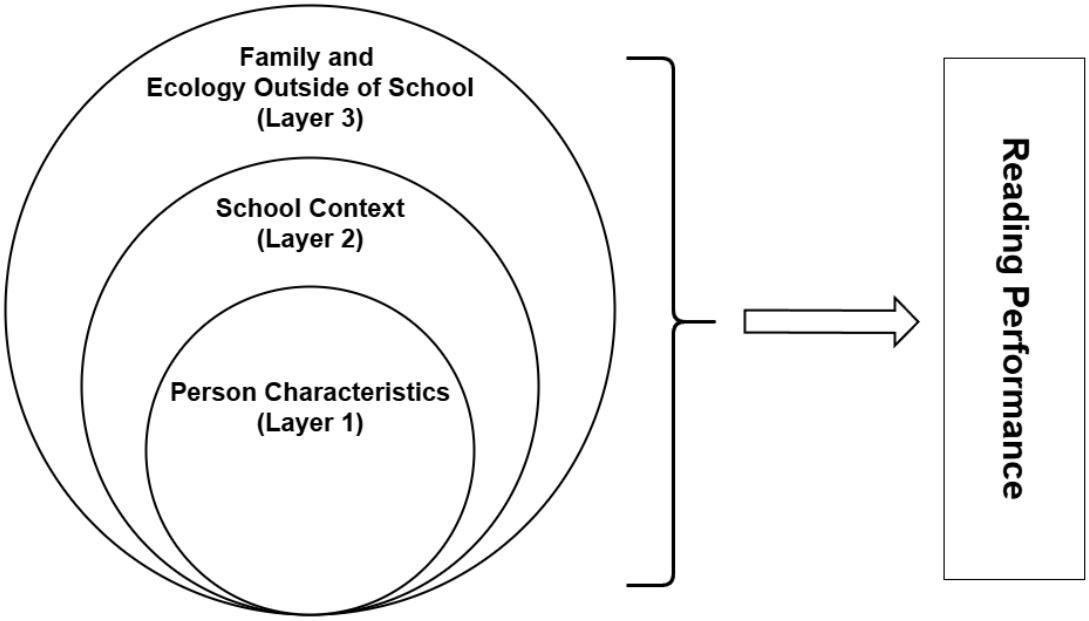

Figure 1. Layers of the Ecological Model Used in the Research

Although Türkiye first participated in PIRLS in 2001, early studies using this dataset remained largely descriptive and lacked theoretical integration. Most focused on surface-level trends or bivariate relationships without considering the broader ecological context (Demirel & Yağmur, 2017; Erman Aslanoğlu & Kutlu, 2015). Even studies examining individual predictors such as self-efficacy, socioeconomic status, or school climate have fallen short of modeling their combined effects. This has left a critical gap in understanding how overlapping influences shape reading achievement—particularly among fourth-grade students, who are especially sensitive to their immediate home and school environments.

The release of PIRLS 2021 presents a timely opportunity to address this gap. With data collected from students, parents, and school administrators, the study offers multi-source insights aligned with Zumbo's model of layered ecological influence (Mullis et al., 2023). Türkiye's reentry into PIRLS enables a fresh analysis situated in updated educational and policy contexts. This study draws on these data to explore the ecological structure of reading achievement in Türkiye, contributing a theoretically grounded perspective to international literacy research.

Method

Research Design

This study is a correlational investigation based on secondary data obtained from the PIRLS 2021 dataset (Fraenkel et al., 2012). Structural equation modeling (SEM) with sampling weights and clustering adjustment at the school level was employed to account for the complex sampling design of PIRLS 2021 (Almaskut et al., 2023; Goldstein et al., 2007). During the analysis, iterative model building and refinement procedures were carried out to comprehensively assess model fit (French & Maller, 2007).

Data Source and Participants

The participants of this study consisted of 6,032 fourth-grade students from Türkiye who took part in the PIRLS 2021 assessment, including 2,989 girls (49.6%) and 3,043 boys (50.4%). Data were collected from students, their parents, and school administrators using standardized questionnaires. Beyond reporting reading scores, PIRLS 2021 also includes extensive contextual data on school and home factors related to performance, including variables concerning family and school contexts (Mullis et al., 2023). The data are publicly available through the IEA website (IEA, 2024b). Prior to conducting the secondary analysis, the PIRLS user manual was consulted to understand the dataset structure, merge relevant files, and ensure that each selected variable accurately represented the intended construct (Mullis, 2019).

Variables and Measures

Data used in this study were obtained from PIRLS 2021, which provides comprehensive information on both students' reading achievement and a range of contextual factors. The analysis focused on three independent variables and one dependent variable. The independent variables were reading self-efficacy (RSE), attitudes toward school (ATS), parents' attitudes toward children's school (PACTS). The dependent variable was reading achievement, operationalized using the five plausible values (PV) provided in the PIRLS dataset.

Information regarding RSE and ATS was collected directly from students, while PACTS data were obtained from parents' responses (Almaskut et al., 2023). All instruments were originally developed in English and adapted to Turkish by the PIRLS national team to ensure cultural and linguistic equivalence (IEA, 2023b). Before analysis, the user manual was consulted to verify variable definitions and coding procedures.

Reading Self-Efficacy (RSE) was measured using six items asking students to rate their perceived competence in reading. The item was: "How well do you read? Tell how much you agree with each of these statements." The statements included both positively and negatively worded items. Attitudes Toward School (ATS) were assessed through six statements reflecting students' perceptions of their school environment. The item was: "What do you think about your school? Tell how much you agree with these statements. Parents' Attitudes Toward Children's School (PACTS) were measured using six items completed by parents. The item was: "What do you think of your child's school?" The full list of items are provided in PIRLS student questionnaire (IEA, 2020).

Each item was measured on a four-point Likert scale ranging from 1 ("Agree a lot") to 4 ("Disagree a lot"). Items with negative wording were reverse coded to ensure that higher scores uniformly reflected greater levels of the underlying construct (Demir, 2020). The dependent variable, reading achievement, was represented by five plausible values calculated for each student by PIRLS, which are recommended for secondary analyses to obtain unbiased estimates (Aparicio et al., 2021).

Data Analysis

Data Preparation

Prior to model estimation, a series of data preparation procedures were conducted to ensure the reliability and integrity of the dataset. First, negatively worded items were identified and reverse-coded in SPSS 29 (IBM, 2021). Specifically, all items measuring *attitudes toward school* (ats) and *parents' attitudes toward children's school* (PACTS) were reverse coded so that higher scores reflected more positive attitudes. Conversely, the items within the *reading self-efficacy* (RSE) scale (ASBR08C, ASBR08D, ASBR08E, and ASBR08F) were already phrased in the negative direction and thus did not require recoding.

Patterns and proportions of missing data were examined using Little's MCAR test. The results indicated a statistically significant outcome, χ^2 (2557) = 3590, $p < .001$, suggesting that the data were not missing completely at random (Kleinke et al., 2020). However, in line with common practice in educational and psychological research, the assumption of missing at random (MAR) was adopted for further analysis (Gomer, 2019). Table 1 presents a summary of missing data proportions and the MCAR test results.

Table 1. Missing Data Analysis

Construct	**Missing Data (%)**	**Little's MCAR Test (χ^2, df, p)**
RSE	1.9–3.1	χ^2 (2557) =3590, p<.001
ATS	1.5–2.2	χ^2 (2557) =3590, p<.001
PACTS	9.4–9.6	χ^2 (2557) =3590, p<.001

Multiple imputation was performed in RStudio using the *mice* package (Buuren & Groothuis-Oudshoorn, 2011). Each construct was defined as a separate imputation block, and predictive mean matching (PMM) was applied as the imputation method. Five imputed datasets were generated, with 50 iterations per imputation cycle to optimize estimation stability (Azur et al., 2011; White et al., 2011). Upon completion, the imputed datasets were integrated into the analysis.

Cronbach's alpha (α) and McDonald's omega (ω) values were calculated to assess the internal consistency of the scales. The initial analysis revealed that the RSE scale had an alpha coefficient below the recommended threshold (α = .50). Item-total correlation analysis indicated that two items (ASBR08A and ASBR08B) had negative corrected correlations. Therefore, these two items were removed from the analysis to protect internal consistency. The revised RSE scale demonstrated improved reliability (α= .71; ω= .77), which was deemed acceptable (Demir, 2020). ATS showed comparatively lower internal consistency than the other scales (α = .67; ω = .68); therefore, findings related to this construct were interpreted with caution. In contrast, PACTS demonstrated strong internal consistency (α = .89; ω = .90). Reporting ω alongside α also provided a more robust basis for evaluating internal consistency (Dunn et al., 2014).

Table 2. Internal Consistency of the Scales

Construct	**Alpha-α**	**Omega-ω**
RSE	.71	.77
ATS	.67	.68
PACTS	.89	.90

Finally, skewness and kurtosis indices were computed for each construct to assess the normality assumptions relevant to SEM. RSE showed no notable departure from normality, whereas ATS and PACTS exhibited negative skewness and elevated kurtosis, indicating ceiling tendencies that are plausible in four-point Likert-type responses. These values exceeded the more conservative benchmarks for substantial non-normality (|skewness| > 2; kurtosis > 7) but remained below Kline's (2015) thresholds for severe non-normality (|skewness| > 3; kurtosis > 10). The results are summarized in Table 3.

Table 3. Skewness and Kurtosis Values

Construct	**Skewness**	**Kurtosis**
RSE	–0.78	–0.04
ATS	–2.18	5.80
PACTS	–2.38	6.86

Multilevel Structural Equation Modeling (SEM)

Multilevel structural equation modeling (SEM) was employed to investigate the relationships among the latent constructs within an ecological framework (Goldstein et al., 2007). Analyses were conducted using the *lavaan* package in RStudio (Rosseel, 2012). Given the complex nature of the dataset, which included clustered observations within schools and a large sample size, robust maximum likelihood estimation (MLR) was selected as the estimation method. MLR was retained because it is appropriate when data show slight to moderate departures from normality (Li, 2016; Maydeu-Olivares, 2017).

The SEM procedure comprised two main stages: confirmatory factor analysis (CFA) and structural modeling. CFA was first used to test whether the observed indicators appropriately represented the latent constructs of reading self-efficacy (RSE), attitudes toward school (ATS), and parents' attitudes toward children's school (PACTS) (Brown, 2023). Subsequently, the structural model was specified to examine the direct effects of these constructs on reading achievement. Five separate SEM models were estimated using each of the five plausible values (PV) as the dependent variable. The parameter estimates and fit statistics were then averaged across the five models to obtain stable results, as recommended in large-scale assessment literature (Aparicio et al., 2021). To further examine assumptions related to the structural model, multicollinearity diagnostics were assessed for the exogenous predictors using factor-level composite scores. The results indicated that multicollinearity was not a concern, as VIF values ranged from 1.008 to 1.030 and tolerance values ranged from .971 to .992 (Demir, 2020).

To improve the representativeness of the results, sampling weights (TOTWGT) were applied

(Mullis, 2019). These weights account for the complex sampling design and ensure that the estimates reflect the population distribution (Almaskut et al., 2023; Pfeffermann, 1996). Additionally, the clustering of students within schools was modeled using school IDs as cluster variables to adjust for the lack of independence among observations (Mullis, 2019). Model fit was evaluated using multiple complementary criteria, including the chi-square statistic (χ^2), comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), standardized root mean square residual (SRMR), goodness-of-fit index (GFI), and adjusted goodness-of-fit index (AGFI). In addition, the Akaike information criterion (AIC), Bayesian information criterion (BIC), and sample-size adjusted BIC (SABIC) were reported as comparative information criteria during iterative model evaluation (Hu & Bentler, 1999; Kline, 2015). Because the chi-square statistic is highly sensitive to sample size and minor model misspecification, it was reported but interpreted cautiously and not used as the sole basis for evaluating model fit (Zheng & Bentler, 2025). CFI and TLI values of .95 or above, RMSEA values of .06 or below, and SRMR values of .08 or below were considered indicative of good fit (Clark & Bowles, 2018; Hu & Bentler, 1999). GFI and AGFI were treated as supplementary indices, with values of .95 and .90, respectively, indicating good fit and lower values of .90 and .85 interpreted more cautiously as acceptable (Schermelleh-Engel et al., 2003). AIC, BIC, and SABIC were used comparatively rather than against fixed cutoffs, with smaller values indicating better fit among competing models (Kline, 2015; Vrieze, 2012)..

Results

Descriptive Statistics

Descriptive statistics were presented to provide a framework of the general distribution and central tendencies of all variables included in the analysis. This step was supported understanding the data structure and evaluating quality prior to model estimation (Cooksey, 2020; Kaur et al., 2018). The results are summarized in four tables, corresponding to the independent and dependent variables. Table 4 presents the descriptive statistics for reading self-efficacy (RSE), attitudes toward school (ATS), parents' attitudes toward children's school (PACTS), and reading achievement. For each latent construct, the item-level scores were averaged to create a factor-level summary. In the case of reading achievement, which is represented by five plausible values (PV1–PV5), the reported descriptive statistics reflect the mean values aggregated across all five PVs.

Table 4. Descriptive Statistics for Variables in Model

Variable	N	Minimum	Maximum	Range	Mean	SD
RSE	6032	1	4	3	2,76	1,06
ATS	6032	1	4	3	3,72	,662
PACTS	6032	1	4	3	3,74	,564
PV	6032	156,1	783,2	627	502,7	85,4

Note. RSE = reading self-efficacy; ATS = attitudes toward school; PACTS = parents' attitudes toward children's school; PV = plausible values aggregated across PV1–PV5; N = sample size; SD = standard deviation.

Descriptive statistics were computed at the factor level instead of the item level to offer a

clearer summary of the model's overall central tendencies. As shown in Table 4, the reading self-efficacy (RSE) construct had a mean of 2.76 (SD = 1.06) on a 4-point scale, suggesting moderately positive self-perceptions among students. Attitudes toward school (ATS) and parents' attitudes toward children's school (PACTS) both exhibited higher means (M = 3.72 and M = 3.74, respectively), indicating generally favorable evaluations of school environments from both students and parents. The plausible values (PV1–PV5) used to represent reading achievement had an aggregated mean of 502.7 and a standard deviation of 85.4, with a broad range of scores (156.1 to 783.2), reflecting substantial variation in reading performance across the sample. Reporting the mean statistics across the five plausible values is consistent with best practices in large-scale assessments, as it enhances the stability and representativeness of the estimates used in the subsequent structural equation modelling (Aparicio et al., 2021).

Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) was performed to assess the measurement model's construct validity and to test the theoretical structure based on Zumbo's ecological framework. Model fit was assessed using multiple indices, including the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The results demonstrated excellent model fit, with values summarized in Table 5. Specifically, the CFA yielded CFI = .99, TLI = .99, RMSEA = .03, and SRMR = .03, alimgning with recommended thresholds for well-fitting models (Shi et al., 2022).

Table 5. Fit Indices

Fit Indices	Value	Structural Model
CFI	.99	.979
TLI	.99	.975
RMSEA	.03	.030
SRMR	.03	.022
CMIN/df		3.79

In addition to reporting global model fit, factor loadings were examined to assess how well each observed item captured its corresponding latent construct. These loadings represent the strength of association between each item and its designated factor (Byrne, 2016). While positive values indicate a direct relationship, negative loadings reflect an inverse association. According to conventional benchmarks, loadings below .30 are considered weak, those between .30 and .50 are acceptable, and values above .50 are deemed strong (Tabachnick & Fidell, 2007). As presented in Table 6, most items demonstrated strong loadings on their intended constructs. Three items—ASBR08C (RSE), ASBG10D (ATS), and ASBG10F (ATS)—had loadings in the acceptable range (.33–.38), suggesting a moderate alignment with their respective factors. The remaining items exhibited high loadings, indicating they were effective indicators of their latent variables. Taken together, these findings confirm that the measurement model possessed satisfactory construct validity, warranting its use in subsequent structural modelling.

Table 6. Standardized Factor Loadings for Each Item

Item Code	RSE	ATS	PACTS
ASBR08C	.33		
ASBR08D	.71		
ASBR08E	.72		
ASBR08F	.69		
ASBG10A		.57	
ASBG10B		.59	
ASBG10C		.55	
ASBG10D		.38	
ASBG10E		.62	
ASBG10F		.35	
ASBH08A			.68
ASBH08B			.66
ASBH08C			.81
ASBH08D			.79
ASBH08E			.80
ASBH08F			.73

Structural Equation Modeling

The structural model was estimated using robust maximum likelihood estimation (MLR), which is well-suited for addressing potential violations of multivariate normality (Maydeu-Olivares, 2017). Model fit indices indicated a good fit to the data: scaled $\chi^2(114) = 432.586$, $p < .001$, CMIN/df = 3.79, CFI = .979, TLI = .975, RMSEA = .030, SRMR = .022, GFI = .999, and AGFI = .999. The comparative information criteria were AIC = 234338.5, BIC = 234711.9, and SABIC = 234534.0. Although the chi-square statistic was statistically significant, this result was interpreted cautiously because of the large sample size. Taken together, the fit indices indicated that the hypothesized model adequately reflected the observed data structure.

Analysis revealed significant paths from all latent variables to reading achievement. Reading Self-Efficacy (RSE) had the strongest standardized regression coefficient ($\beta = .446$, $p < .001$), indicating a substantial positive effect. Attitudes toward school (ATS) also exhibited a positive and statistically significant effect ($\beta = .118$, $p < .001$), while parents' attitudes toward children's school (PACTS) had a weaker but still significant positive effect ($\beta = .080$, $p < .001$). Together, the predictors explained 23.9% of the variance in reading achievement ($R^2 = .239$).

Covariance relationships among the predictors were also examined. RSE and ATS showed a positive value ($r = .224$, $p < .001$), whereas ATS and PACTS were negatively covariated ($r = –.111$, $p < .001$). The covariance between RSE and PACTS was not statistically significant ($r = –.027$, $p = .191$), suggesting that parental attitudes may exert their influence indirectly rather than through direct association with students' self-efficacy.

These standardized structural path coefficients suggest a hierarchical pattern in predictive strength: RSE emerged as a strong predictor, whereas ATS and PACTS showed comparatively small effects. Thus, although both coefficients were statistically significant, their practical importance was more limited than that of RSE (Kline, 2015). All structural path coefficients from the latent predictors to reading achievement were statistically significant at $p < .001$. Covariance estimates were interpreted separately: the covariance between RSE and ATS ($r = .224$, $p < .001$) and the covariance between ATS and PACTS ($r = –.111$, $p < .001$) were statistically significant, whereas the covariance between RSE and PACTS was not ($r = –.027$, $p = .191$). Figure 2 presents the final structural model, including standardized path coefficients and covariance estimates. Asterisks (*) indicate statistical significance at $p < .001$. Collectively, findings highlight personal factors, particularly self-efficacy, in reading achievement, while school and parental attitudes contribute more modestly. This pattern supports the ecological perspective that academic outcomes are best understood through the interplay of multiple contextual influences.

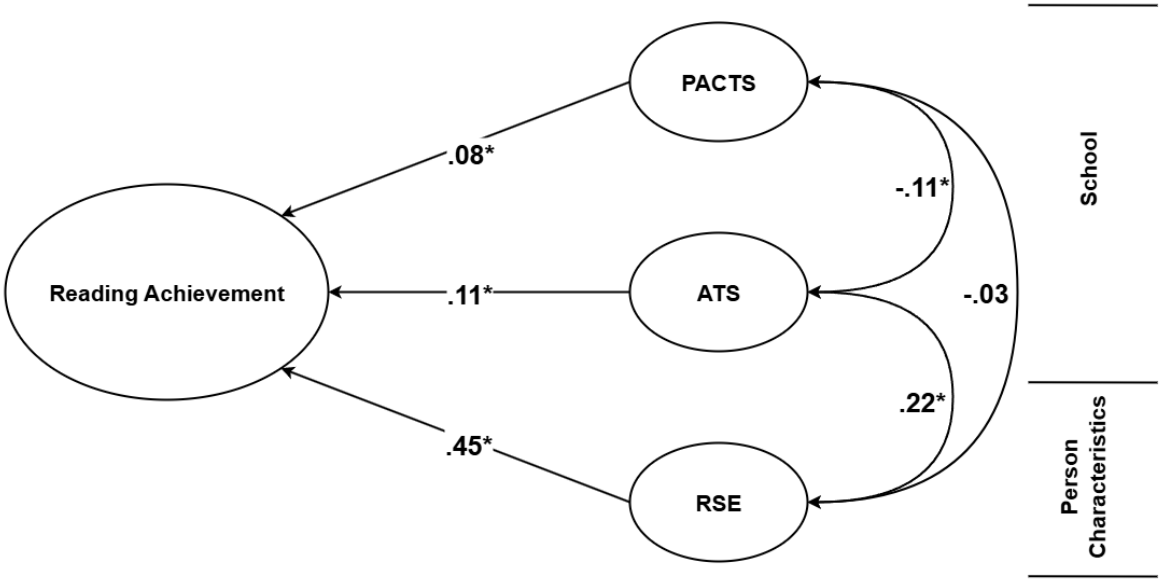

Figure 2. Structural Equation Modeling

Discussion

This study explored how personal, school, and family-level factors interact to shape reading achievement among fourth-grade students in Türkiye, using Zumbo's ecological framework as a theoretical lens. By employing structural equation modeling with nationally representative PIRLS 2021 data, the findings offer an integrated view of the multilayered influences that contribute to reading performance. Consistent with the ecological approach, each of the three predictors—reading self-efficacy, students' attitudes toward school, and parents' attitudes toward their child's school—exerted significant effects, though their magnitudes varied. Reading self-efficacy emerged as the most influential factor, underscoring the central role of students' self-perceptions in literacy outcomes. Attitudes toward school

also had a meaningful positive effect, highlighting the importance of emotional and social connectedness within school settings. In contrast, parental attitudes demonstrated a more modest yet statistically significant impact, suggesting a complementary role at the family level.

In addition to their individual contributions, these variables interacted through notable covariance relationships. The strongest of these was observed between reading self-efficacy and school attitudes, indicating shared internal dynamics that may reinforce one another. Meanwhile, the relationship between school and parental attitudes revealed a slight negative association, inviting further exploration of context-specific dynamics in home-school alignment. No significant association was found between reading self-efficacy and parental attitudes, suggesting independent pathways of influence. The sections that follow examine these results in greater depth, organized by the three ecological layers proposed in the model: personal characteristics, school context, and family influences. Each subsection interprets the respective factor's predictive strength, contextual relevance, and interaction with other variables—contributing to a holistic understanding of how reading achievement is shaped across ecological domains.

Personal Characteristics Layer Results: Reading Self-Efficacy

Among the factors examined in this study, reading self-efficacy (RSE) demonstrated the strongest predictive effect on reading achievement ($\beta = 0.45$). This finding is consistent with previous research underscoring the critical role of self-efficacy in academic performance. Reading self-efficacy, in particular, shapes students' early literacy experiences by influencing their motivation, persistence, and confidence when engaging with reading tasks (Lee & Jonson-Reid, 2016). Prior studies consistently report that students with higher self-efficacy are more enthusiastic about reading, persevere through challenges, and perform better in comprehension and fluency (Göktentürk et al., 2023).

In the Turkish educational context, evidence from PIRLS (2001, 2021) suggests a noticeable increase in students' reading self-efficacy over the past two decades (Mullis et al., 2003, 2023). This positive trend can be attributed to national education policies focusing specifically on early literacy development (MEB, 2006, 2019). Furthermore, recent curriculum changes in Türkiye have placed greater emphasis on enhancing students' self-beliefs and attitudes toward learning, which is a possible contribution to this improvement (MEB, 2024). Therefore, this study's findings support existing recommendations to incorporate strategies targeting reading self-efficacy into literacy instruction, which could effectively promote better reading outcomes.

School Layer Results: Attitudes Toward School

Attitudes toward school (ATS) also emerged as a significant predictor of reading achievement, although the strength of this relationship ($\beta = 0.11$) was lower compared to self-efficacy. Although this coefficient indicates a relatively limited practical effect size, it still suggests that students' positive perceptions of the school environment contribute meaningfully to reading achievement within the broader ecological model (Kline, 2015). According to prior research, students who experience a sense of belonging, safety, fairness, and pride in their school typically show higher engagement, motivation, and academic achievement (Psathiti & Sailer, 2023).

Students' attitudes toward school affect their academic performance directly through

emotional and social engagement and indirectly through increased participation in learning activities (Fredricks et al., 2004; Hughes et al., 2015). For instance, when students perceive positive teacher behaviors, fair classroom practices, and supportive peer relationships, their motivation for reading and overall school participation tend to increase (Ma et al., 2021). This aligns with Zumbo's ecological model, highlighting the interconnectedness of various educational factors that influence student attitudes (Göktentürk et al., 2023; Zumbo et al., 2015). Thus, developing positive school climates and encouraging teacher-student relationships can effectively support students' reading development and overall academic success.

Family Layer: Results Parents' Attitudes Toward School

Parents' attitudes toward their children's school (PACTS) significantly predicted reading achievement as well, albeit with a weaker direct effect ($\beta = 0.08$). This coefficient reflects a relatively small practical contribution; however, its statistical significance supports the view that parental attitudes still form part of the broader constellation of ecological influences on reading achievement (Kline, 2015). According to previous literature, parental attitudes significantly affect children's academic motivation and engagement indirectly by shaping home-based literacy practices and expectations about school success (Ding et al., 2022).

Parents who hold positive attitudes toward their children's school generally provide stronger support for academic activities, communicate more frequently with teachers, and participate more actively in school events (Yang et al., 2023). Such parental engagement consistently promotes better student outcomes, including improved reading skills (Stoeger et al., 2014). Thus, although the direct predictive power of parental attitudes was comparatively modest, their indirect influence through interactions with personal and school-related factors is crucial. Educational interventions aiming to boost reading achievement should therefore actively engage parents, emphasizing positive home-school partnerships within an ecological framework.

Relationships between the Factors Composing the Independent Variables

A key benefit of employing an ecological model in this study is that it considers how independent variables interact and collectively influence reading achievement. The strongest observed covariance was between reading self-efficacy (RSE) and attitudes toward school (ATS) ($r = 0.22$). This significant relationship implies that students who perceive themselves as capable readers are also more likely to hold positive attitudes towards their school. Previous studies confirm that higher levels of self-efficacy are often associated with greater school engagement and participation in learning activities (Ebere Adimora et al., 2019; Kurniawan et al., 2021). Given that both RSE and ATS are self-reported by students, this strong covariance likely reflects the common internal, personal perspective shaping both constructs.

The covariance between ATS and parents' attitudes toward school (PACTS) was weaker and negative ($r = -0.11$), an initially surprising result. Typically, literature suggests that parents' positive attitudes toward school enhance children's school-related attitudes (Popa, 2020; Williams, 2017). However, the slight negative correlation found here raises an alternative possibility: excessively high parental expectations or pressure might inadvertently lead students to develop less positive school attitudes (You et al., 2016). Nevertheless, the existing research generally emphasizes the positive impact of supportive parental attitudes on

children's educational outcomes, suggesting that this weak negative correlation might be context-specific and requires further investigation.

Notably, there was no significant covariance between RSE and PACTS (r = -0.03), indicating these factors independently influence reading performance. This suggests that parental attitudes toward school affect reading achievement without directly impacting children's perceptions of their reading capability. While some prior studies found weak but meaningful links between parental involvement and children's self-efficacy (Fan & Williams, 2010), others support the notion that family influences, while important, do not directly shape specific self-efficacy beliefs (Norudin et al., 2024). The present study aligns with these findings, highlighting the importance of separately addressing family support and self-efficacy within educational interventions. Overall, the significant relationships identified among RSE, ATS, and PACTS emphasize the importance of examining reading achievement within an ecological framework. Recognizing these interactions allows educators and policymakers to implement more comprehensive interventions that simultaneously target personal, school-related, and familial factors influencing reading outcomes.

Conclusion

This study identified a well-fitting ecological structural equation model for explaining fourth-grade reading achievement in Türkiye. The findings showed that reading self-efficacy, attitudes toward school, and parents' attitudes toward children's school all significantly predicted reading achievement, thereby supporting the proposed ecological model. Among these predictors, reading self-efficacy emerged as the strongest contributor, whereas attitudes toward school and parents' attitudes toward children's school had weaker but significant effects. These results indicate that reading achievement is shaped not only by students' personal beliefs, but also by school- and family-related conditions within a broader ecological context. Overall, the findings suggest that efforts to improve reading achievement in Türkiye should prioritize students' reading self-efficacy while also supporting positive school climates and constructive home–school relationships.

Limitations

While the current research contributes important insights, certain methodological and contextual limitations warrant consideration. First, this study was structured within an ecological framework; however, the independent variables in the model are limited to those available in the PIRLS 2021 dataset. It is always possible that unmeasured confounding variables, which were not included in the study but may influence the results, exist (Andrade, 2024).

Second, the study focused solely on fourth-grade students in Türkiye. Consequently, the findings may not be generalizable to other age groups or educational contexts. The developmental stage of younger children means that the relative influence of ecological factors may differ substantially in later schooling years (Subotnik et al., 2019; Taylor et al., 2020).

Third, variables such as reading self-efficacy and attitudes toward school, obtained from students, as well as parental attitudes toward school, obtained from parents, were collected through self-report measures in the PIRLS questionnaires. The analyses were conducted based on the assumption that the responses provided by students and parents to the questionnaire items were accurate and free from bias (Chandler & Paolacci, 2017).

Finally, since this study utilizes data from PIRLS 2021, which represents a snapshot in time, the directionality and causal inferences regarding the relationships between variables may be limited. Although structural equation modelling reveals correlational relationships, establishing definitive cause-and-effect links between variables is not possible due to the inherent nature of the study.

Recommendations for Future Research and Educational Practice

The findings of this study demonstrate that reading self-efficacy, students' attitudes toward school, and parents' attitudes toward children's school do not operate in isolation but interact within an ecological framework. This multi-layered perspective offers valuable insights for researchers, practitioners, and policymakers alike. While this study focused on three key predictors within a structural equation modeling (SEM) framework, the PIRLS dataset includes additional variables such as digital literacy, instructional practices, and peer interactions. However, these variables were not incorporated into the model due to the analytical features of SEM; an issue that could be addressed in future research through hierarchical linear modeling (HLM).

Furthermore, expanding Zumbo's ecological model to encompass its full range of contextual layers-including institutional, curricular, and community-level factors—would enhance its explanatory power and support more robust inferences across age groups and cultural contexts. Applying this broader framework to other educational levels and diverse populations could reveal whether the observed ecological patterns are consistent or vary according to developmental and contextual factors.

From a policy perspective, these findings suggest that decision-makers should consider ecological principles when designing educational strategies. Rather than developing direct intervention models themselves, policymakers can support the integration of ecological thinking into curriculum reforms, teacher development programs, and school climate initiatives. For instance, the "2024 Maarif Model" introduced by Republic of Turkiye Ministry of National Education explicitly emphasizes both personal and social-emotional competencies; a promising shift that aligns with ecological priorities.

At the classroom and school level, teachers, administrators, and counselors should be aware of the interaction between students' self-beliefs and their attitudes toward school. Programs aiming to boost reading self-efficacy are likely to be more effective when paired with efforts to create safe, inclusive, and motivating school environments. Moreover, fostering strong school–family partnerships remains vital. The observed association between parents' attitudes and students' school engagement suggests that schools should actively involve families through transparent communication, shared responsibility, and inclusive practices.

Finally, international assessments such as PIRLS should continue to support research grounded in ecological frameworks by ensuring that their datasets remain rich in contextual indicators. Türkiye's re-participation in PIRLS after a two-decade hiatus represents a valuable opportunity to monitor educational trends over time. Regular engagement in such studies can facilitate data-driven policy development, especially when findings are interpreted through comprehensive ecological lenses like Zumbo's model. Future studies should aim to explore the full complexity of this model by including variables from each of its ecological layers.

Declarations

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