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ICT Access and Inequality in Global Reading Achievement: Cross-Level Interactions and Compensatory Effects in PISA 2018

Nirmal Ghimire[1], Sushila Regmi[2]

[1]Watson College of Education, University of North Carolina Wilmington, USA

[2]Department of Social Sciences, Oslo Metropolitan University, Oslo, Norway

Correspondence: Nirmal Ghimire, TESL Program, Education Building (EB345), Watson College of Education, University of North Carolina Wilmington, Wilmington, NC 28403, USA. https://orcid.org/0000-0002-2032-1624

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Abstract

This study analyzed Programme for International Student Assessment (PISA) 2018 data (N = 612, 004 students across 79 countries) using hierarchical linear modeling to examine relationships between information and communication technologies (ICT) and reading achievement. Student-level predictors included home access, skills, attitudes, and usage patterns; school-level factors comprised infrastructure, resources, and classroom integration. Findings revealed complex relationships with student-level factors, with home access and perceived competence showing positive associations but excessive academic technology use relating negatively to reading scores. Country-level analysis demonstrated that ICT resource inequality correlated negatively with reading achievement regardless of absolute resource levels. Most significantly, cross-level interactions indicated compensatory rather than amplifying effects, with home technology access showing stronger positive associations with reading achievement in technology-poor schools. These findings challenge concerns that educational technology inherently widens achievement gaps and suggests strategic resource allocation could potentially narrow disparities. Results support a nuanced perspective toward technology in education, emphasizing equitable distribution and context-specific implementation rather than universal approaches to digital integration.

Keywords: reading achievement, digital divide, PISA, hierarchical linear modeling, home technology access, cross-level interactions, educational technology

1. Introduction

As education systems globally undergo digital transformation, information and communication technologies (ICT) have become deeply embedded in teaching and learning processes. This trend has accelerated with recent shifts towards online and blended learning environments, making it imperative to understand the full spectrum of ICT's influence on educational outcomes, particularly with reading achievement, a foundational skill for academic success across disciplines.

The relationship between ICT and student outcomes remains contested territory (Aesaert et al., 2017; Arpaci et al., 2021, Ghimire & Mokhtari, 2025). While some studies demonstrate that targeted technology use can enhance ? (Gomez-Fernandez & Mediavilla, 2021), others caution against excessive or unguided technology integration, highlighting its potential negative effects on learning (Gubbels et al., 2020; Huang et al., 2021). These conflicting findings suggest that technology's relationship with learning is neither uniform nor straightforward, but rather context-dependent and multidimensional.

This complexity is further evident in the evolving conceptualization of digital divides. Research has progressed from examining simple access gaps (first-level divides) to exploring disparities in effective usage (second-level divides) and ultimate benefits (third-level divides) (Vaj Dijk, 2020). Similarly, investigations of ICT in education have expanded from counting devices to examining how technologies are distributed, implemented, and experienced across diverse educational contexts (Reich, 2020).

The present study addresses several critical gaps in current understanding of ICT's relationship with reading achievement. First, although PISA and other large-scale assessments provide rich multilevel data, many analyses fail to simultaneously model student, home, and school technology factors, instead examining these levels in isolation (Hu & Yu, 2021). Second, research often focuses on absolute technology levels without considering distributional patterns within educational systems, potentially missing important equity dimensions (Agasisti et al., 2023). Third, cross-level interactions, particularly the ways home and school technology environments might complement or compensate for one another, remain underexplored, despite growing recognition of their importance in ensuring equitable educational outcomes (U.S. Department of Education, 2023).

Our study addresses these gaps through a comprehensive multilevel analysis of the 2018 PISA data, encompassing 612,004 students across 79 countries. We utilized hierarchical linear modeling with appropriate sampling weights to examine how student-level factors (home access, perceived competence, interest, usage patterns), school-level factors (infrastructure, resources, classroom integration), and their interactions relate to reading achievement. Additionally, we investigate how within-country inequality in technology resources relates to national reading outcomes, a dimension rarely addressed in international comparative research.

This approach allows us to move beyond the question of whether technology "works" to a more nuanced exploration of when, how, and for whom different technological configurations relate to reading achievement. By examining potential compensatory or amplifying effects across levels, we contribute to both theoretical understanding of educational technology's role in literacy development and identify practical considerations for more equitable technology implementation in diverse global contexts.

2. Literature Review

2.1 Digital Divides and Technology in Education

The impact of information and communication technologies (ICT) on student outcomes remains debated with mixed evidence (Gomez-Fernandez & Mdeiavilla, 2021; Hu & Yu, 2021). Research has evolved from examining simple access gaps to investigating more complex relationships between technology and learning, mirroring the conceptual evolution of digital divides from first-level concerns about physical access to second-level usage of quality and third-level outcome benefits (van Dijk, 2020). By 2018, the access gap had narrowed considerably, with 99% of advantaged versus 94% of disadvantaged 15-year-olds having home internet access across OECD countries (OECD, 2022).

Studies supporting positive technology effects typically highlight contexts with targeted implementation, finding that well-structured ICT integration can improve learning experiences and outcomes (Petko et al., 2017; Srijamdee & Pholphirul, 2020), while emphasizing that benefits depend less on technology presence than on implementation quality, with teacher guidance emerging as a critical mediating factor (Lezhnina & Kismihok, 2022; Sanfo, 2023). Conversely, research documenting negative or null relationships has identified mechanisms through which technology might hinder learning, including distraction effects and cognitive overload (Gubbels et al., 2020; Huang et al., 2021).

2.2 ICT and Reading Achievement: Complex Relationships

The relationship between ICT factors and reading literacy presents a nuanced picture with significant contextual variation. Home access to computers and the internet has shown positive correlations with reading achievement, but research suggests these benefits plateau beyond certain threshold (Lee & Wu, 2012; Bhutoria & Aljabri, 2022). Recent research using 2018 PISA data highlights the complexity, with Ghimire and Mokhtari (2025) finding a positive association between home ICT access and reading scores while also identifying a curvilinear relationship where moderate ICT usage was most beneficial for achievement.

Studies investigating technology use patterns have revealed important distinctions between types of engagement. Recreational internet use often correlates positively with literacy levels (Hu & Yu, 2021), while academic applications frequently show negative or null relationships, particularly without adequate structure (Gomez-Fernandez & Mediavilla, 2021). This paradoxical pattern suggests self-directed, interest-driven technology use may benefit literacy development than formally assigned digital tasks.

Home technology's relationship with reading shows contextually-dependent patterns (Lee & Wu, 2012) with significant variation based on implementation quality. Steffens (2014) cautions against unsupervised high-frequency ICT use, while Li and Petersen (2022) demonstrate that intrinsic motivation drives effective technology use more powerfully than mere technology availability.

Both perceived and actual ICT competencies significantly influence reading performance, with students who view themselves as technologically competent generally achieving higher reading scores across various national contexts (Aesaert et al., 2017; Rohatgi et al., 2016). The sociocultural context surrounding technology uses introduces additional complexity, with regional differences in ICT development stages creating varied baselines for technology integration (Erdogdu & Erdogdu, 2015; Meng et al., 2019).

2.3 Multilevel Perspectives and Cross-Level Interactions

Educational technology environments operate across multiple interconnected levels, with student, home, classroom, school, and system factors jointly shaping how technology relates to learning outcomes. Individual characteristics like motivation, and technology attitudes significantly moderate ICT effects (Kong et al., 2022), while home technology environments, including parental mediation and digital cultural capital, create foundations that influences educational engagement (Zheng et al., 2022).

School-level factors introduce additional variation through differences in infrastructure quality, teacher professional development, and technology integration models. Schools with substantial technical resources but limited pedagogical support often show disappointing returns on technology investments (Comi et al., 2017). Conversely, schools with modest infrastructure but strong implementation strategies sometimes achieve more positive outcomes, highlighting the primacy of pedagogical approaches over equipment provision (Tondeur et al., 2020).

These influences may either reinforce disparities through amplification effects, where technology primarily benefits already-advantaged students (Reich, 2020) or follow compensatory patterns where resources in one context offset limitations in another (Camerini et al., 2018). Warschauer and Matuchniak (2010) emphasize the ‘quality of use’ often matters more than access alone. Despite recognition of these multilevel influences, research examining cross-level interactions between home and school technology environments remains surprisingly limited, particularly in international comparative contexts (Camerini et al., 2018; Reich, 2020).

2.4 Technology Distribution and Contextual Factors

Beyond individual and institutional factors, system-level characteristics, particularly the distribution of technological resources, influence how ICT relates to educational outcomes. Emerging research suggests that inequality in technology resources within educational systems may undermine overall performance regardless of average resource levels (Agasisti et al., 2023). This parallel findings on other educational inputs, where equitable distribution often correlates with stronger system-wide outcomes (OECD, 2018).

Cultural contexts further shape technology-learning relationships through varied educational policies, implementation approaches, and social norms surrounding digital media. Comparative studies reveal substantially different patterns in how similar technologies relate to achievement across different cultural contexts (Lafontaine et al., 2015) with resource distribution patterns often mattering more than raw technology access (Zhang & Liu, 2016). The methodological approaches used to examine these relationships have evolved considerably, with increasing recognition of the need for multilevel modeling techniques that properly account for nested data structures. Particularly when analyzing large-scale assessments like PISA, appropriate handling of weighting procedures becomes essential for generating valid inferences about population relationships (Gard et al., 2023; West et al., 2015).

2.5 Moderating Factors in Technology’s Educational Impact

The relationship between educational technology and reading outcomes is moderated by several important factors that help explain varying results across studies and contexts. Student characteristics play a critical role, with digital literacy, general academic ability, and gender all influencing how technology relates to learning outcomes. Students with higher baseline digital skills often drive greater benefits from educational technology, potentially creating Matthew effects – where initial advantages compound over time, causing growing disparities—where technology accelerates learning for already-advantaged students (Rohatgi et al., 2016). Gender differences also appear consistently, with distinct patterns of technology engagement and different relationships between ICT use and achievement for boys versus girls (OECD, 2021).

Teacher-related factors substantially moderate technology’s educational impact through variations in technological pedagogical content knowledge, instructional approaches, and implementation quality. Teacher confidence with technology emerges as a particularly strong predictor of successful integration, often outweighing hardware availability in determining outcomes (Dexter & Richardson, 2019). Professional development focused on pedagogical uses of technology rather than mere technical skills shows stronger relationships with student achievement, highlighting the crucial mediating role teachers play in translating technological capabilities into learning benefits (Tondeur et al., 2020).

Sociocultural factors introduce additional complexity through varying attitudes toward technology, cultural capital related to digital practices, and differing parental mediation approaches. Family technology norms and values significantly influence how students engage with digital tools for learning, potentially reinforcing or mitigating socioeconomic disparities (Zheng et al., 2022). Parental guidance regarding technology use shows significant associations with both the quantity and quality of students’ digital learning activities, suggesting that home digital culture serves as an important moderating influence (Camerini et al., 2018).

Family technology practices significantly impact student engagement (Zheng et al., 2022). Pedagogical implementation quality strongly moderates outcomes, with teacher knowledge often predicting success better than equipment availability (Dexter & Richardson, 2019). Approaches enhancing critical digital literacy (Buckingham, 2021), specific instructional strategies (Coiro, 2020; Singer & Alexander, 2017), authentic tasks (Ito et al., 2018), and collaborative environments

(Greenhow & Askari, 2017) collectively determine whether technology translates into learning benefits (Darling-Hammond et al., 2017; Reich & Ito, 2017).

Most significantly for policy considerations, evidence increasingly suggests that the relationship between technology and achievement follows different patterns across resource contexts. In technology-rich environments, the quality of usage emerges as the primary determinant of educational benefits, while in resource-constrained settings, basic access still shows meaningful relationships with outcomes (Arpaci et al., 2021).

2.6 Conceptual Background and the Purpose of the Study

This study integrates multiple theoretical frameworks to examine how ICT's influence on reading achievement across diverse global contexts. We draw on digital divide perspectives that have evolved from binary access concerns (Warschauer, 2002) to multilevel conceptualizations of access, skills, and outcomes (van Dijk & Hecker, 2003). We also incorporate education production function frameworks (Hanushek, 2020), examining not just technology's presence but its distribution, particularly how resource inequality might undermine system performance (Agasisti et al., 2023).

Central to our analysis are competing perspectives on technology's equity implications: the "amplification" view suggesting technology disproportionately benefits advantaged students (Reich, 2020) versus the "compensatory" perspective positing resources in one context might offset limitations in another (Camerini et al., 2018). We ground our approach in sociotechnical systems theory, recognizing the technology's influence depends on its integration within social and institutional contexts (Tondeur et al., 2020).

Using PISA 2018 data from 79 countries, this study addresses limitations in previous research that often examined limited geographical areas or specific variables (Cho et al., 2016). We incorporate weighted sampling in our hierarchical analysis, addressing a common oversight in large-scale assessment research (Gard et al., 2023; West et al., 2015) and mitigating biases associated with neglecting sampling weights in multilevel modeling (OECD, 2009). To provide a comprehensive framework for this inquiry, we pose the following research questions:

1. How do student-level ICT factors (home access, competence, interest) relate to reading achievements across global contexts?
2. To what extent does ICT resource inequality at the country level explain variation in reading outcomes beyond absolute resource levels?
3. How do student-level and school-level ICT factors interact to influence reading achievement, and do these interactions indicate compensatory or amplifying effects?

3. Methodology

3.1 Data Sources & Participants

This study utilized data from the Program from International Student Assessment (PISA) 2018 cycle which focused on reading literacy as its primary domain. PISA is conducted by the Organization for Economic Co-operation and Development (OECD) to assess 15-year-old students' knowledge and skills in reading, mathematics, and science, along with contextual information about students, schools, and educational systems.

The PISA sampling design employs a two-stage stratified approach. Schools are first selected systematically from a comprehensive list of eligible schools in each education system with probabilities proportional to size (PPS). Subsequently, eligible 15-year-old students are randomly sampled from within the selected schools. This approach ensures the sample represents the full population of schools and 15-year-old students in each participating education system (OECD, 2019).

Our analysis included all available data from students who participated in the PISA 2018 assessment and completed the ICT questionnaires across 79 countries/economies. The initial dataset comprised 612,004 students from 21,903 schools. After accounting for missing data on key ICT variables, our analytical sample included 288,489 students (47.1% of the initial sample) from 13,509 schools (61.7% of the initial sample) across 52 countries (65.0% of the initial sample). Sensitivity analysis comparing key characteristics between the analytical sample and the full sample suggested minimal systematic differences, though we acknowledge this reduction in sample size as a limitation.

The pooled international dataset provides a robust, internationally comparable sample representing approximately 28 million 15-year-old students enrolled in grade 7 or higher across participating countries. Table 1 presents the distribution of students, schools, and weighted sample size by country.

3.1.1 ICT Variables and Measurement

The study incorporated multiple ICT-related measures at the student and school levels, derived from the PISA student and school questionnaires. All indices were constructed using standardized methodologies by the OECD and underwent validation procedures to ensure cross-cultural comparability.

3.1.2 Student-Level ICT Variables

- ICT Availability at Home (ICTHOME): measures students' access to technological devices at home (range: 0-11). Higher values indicate greater access indicating a first-level digital divide indicator.
- Perceived ICT Competence (COMPICT): COMPICT is a standardized index (mean = 0, SD = 1 across OECD countries) capturing students' self-reported ability to perform digital tasks independently. Higher values indicate greater self-reported digital competence, representing a second-level digital divide indicator focusing on skills and capabilities.
- Interest in ICT (INTICT): Standardized index measures students' interest and engagement with technology. Constructed from responses about enjoyment, interest, and perceived importance of ICT.
- ICT Use for School-Related Tasks at Home (HOMESCH): Standardized index measuring frequency and diversity of technology use for educational purposes outside school hours.

3.1.3 School-Level ICT Variables

- School ICT Infrastructure (ICTSCH): Measures technological infrastructure availability within schools (range: 0-10), based on students' reports. Higher values indicate more extensive infrastructure.
- ICT Resources (ICTRES): Standardized index measuring quality and sufficiency of technological resources at schools. Unlike ICTSCH, it incorporates information about maintenance quality, technical support, and teacher training resources. Higher values indicate better quality and more sufficient technological resources.
- ICT Classroom Integration (ICTCLASS): Standardized index measuring extent of technology incorporation into regular classroom practices.

3.1.4 Reading Achievement Measure

Reading achievement was measured using the ten plausible values provided in the PISA 2018 dataset (PV1READ – PV10READ). The PISA reading scale has a mean of 500 and standard deviation of 100 across OECD countries, with higher values indicating better reading performance.

3.1.5 Derived Country-Level Measures

In addition to the PISA-provided indices, we constructed several country-level measures to examine distributional patterns and national contexts.

- ICT Resource Inequality: For each country, we calculated the difference between the 90th and the 10th percentiles of the ICTRES distribution, creating an inequality index that captures the gap between the most and least resourced schools within each educational system. Higher values indicate greater disparity in technology resources across schools.
- Mean ICT Resources: This country-level measure represents the average standardized scores on the ICTRES index across all schools within a country, serving as an indicator of the overall level of technological resourcing in a national educational system.
- Mean School ICT Infrastructure: Similar to mean ICT resources, this measure represents the average ICTSCH score across all schools within a country, providing an indicator of the typical infrastructure level in each national system.

3.2 Analytical Approach

Our analysis employed hierarchical linear modeling (HLM) to account for the nested structure of students within schools within countries. We used the {lme4} package (Bates et al., 2015) in R (R Core Team, 2025) for all models, with appropriate weighting to account for PISA's complex sampling design.

3.3 Model Building Strategy

We used a sequential model-building approach to address our research questions:

a. Null Model with random intercepts for school and countries:

$$Y_{ijk} = \beta_0 + u_{0i} + v_{0ij} + \varepsilon_{ijk} \tag{1}$$

Where, Y_{ijk} represents the reading score for student *k* in school *j* in country *i*; β_0 is the overall intercept; u_{0i} is the country-level random effect; v_{0ij} is the school-level random effect; and ε_{ijk} is the residual error.

b. Fixed Effects Model incorporating all student and school-level ICT predictors:

$$\mathrm{Y}_{ij} = \beta_0 + \beta_1 .\{ICTHOME\}_{ijk} + \beta_2 .\{COMPICT\}_{ijk} + \beta_3 .\{INTICT\}_{ijk} + \beta_4 .\{HOMESCH\}_{ijk} + \beta_5 .\{ICTSCH\}_{ijk} + + \beta_6 .\{ICTRES\}_{ijk} + + \beta_7 .\{ICTCLASS\}_{ijk} + u_{0i} + v_{0ij} + \varepsilon_{ijk} \tag{2}$$

c. Random Slope Testing for each predictor, comparing models with likelihood ratio tests:

$$Y_{ijk} = \beta_0 + \beta_1\, ICTHOME_{ijk} + \cdots + \left[u_{0i} + v_{0ij} + v_{1ij} ICTHOME_{ijk}\right] + \varepsilon_{ijk} \tag{3}$$

Where v_{1ij} represents the random slope for ICTHOME at the school level.

d. Random Slopes for all seven ICT predictors at the school level:

$$Y_{ijk} = \beta_0 + \beta_1\, ICTHOME_{ijk} + \cdots + \beta_7\, ICTCLASS_{ijk} + \left[u_{0i} + v_{0ij} + v_{1ij} ICTHOME_{ijk} + \cdots + v_{1ij} ICTCLASS_{ijk}\right] + \varepsilon_{ijk} \quad (4)$$

e. Cross-Level Interaction Model including key interactions between student and school ICT factors:

$$\mathrm{Y}_{ijk} = \beta_0 + \beta_1 . \mathrm{ICTHOME_{ikj}} + \beta_2 . \mathrm{COMPICT_{ikj}} + \beta_3 . \mathrm{INTICT_{ijk}} + \beta_4 . \mathrm{HOMESCH_{ijk}} + \beta_5 . \mathrm{ICTSCH_{ijk}} + \beta_6 . \mathrm{ICTRES_{ijk}} + \beta_7 . \mathrm{ICTCLASS_{ijk}} + \beta_8 . \mathrm{ICTHOME_{ijk}}\ \mathrm{X}\ \mathrm{ICTSCH_{ijk}} + \beta_9 . \mathrm{COMPICT_{ijk}}\ \mathrm{X}\ \mathrm{ICTRES_{ijk}} + \beta_{10} . \mathrm{INTICT_{ijk}}\ \mathrm{X}\ \mathrm{ICTCLASS_{ijk}} + \mathrm{u_j} + \mathrm{v_k} + \varepsilon_{\mathrm{ijk}} \quad (5)$$

The outcome Y_{ikj} is the reading score for student *i* in school *k* in country *j*. Fixed effects β_0 to β_7 represent main effects, while β_8 to β_{10} capture interaction terms. The model includes random effects for schools v_k and countries u_j to account for nesting. Residual errors are ε_{ijk}.

3.4 Other Considerations

Because PISA provides reading achievement as ten plausible values (PV1READ-PV10READ), we estimated each model separately for each plausible value. Parameter estimates and standard errors were then pooled following Rubin's rule for multiple imputation (Rubin, 1987), accounting for both with-in imputation and between-imputation variation components.

To account for PISA's complex sampling design, we applied the student final weight (W_FSTUWT) in all analyses, enabling population-representative estimates for approximately 28 million 15-year-old students represented in the sample. This approach aligns with recommendations for analyzing large-scale assessment data (Rutkowski et al., 2010).

To identify patterns in how countries organize their technological resources, we conducted a descriptive analysis plotting mean ICT resources against mean school ICT infrastructure at the country level. We then categorized countries based on their OECD membership status and examined clustering patterns visually, with point size representing mean reading achievement to identify associations between ICT profiles and educational outcomes.

To investigate the relationship between ICT resource and distribution and reading achievement, we conducted correlation and regression analyses between our constructed inequality index and country-level mean reading scores. We controlled for country-level economic development (using OECD status as a proxy) to examine whether the relationship persisted beyond general economic factors.

Missing data were present for several ICT variables, primarily because some countries did not administer certain questionnaire components or because individual students did not complete all items. Rather than imputing missing values, which could introduce bias given the multilevel structure and substantial between-country variation, we employed a complete-case analysis approach for the primary models.

To assess the potential bias from this approach, we conducted sensitivity analyses comparing key demographic characteristics and reading scores between analytical sample and the full sample. While some minor differences were observed, they were not systematic enough to suggest substantial selection bias. Nevertheless, we acknowledge this reduction in sample size as a limitation of our study and discuss its implications in the limitations section.

All analyses were conducted using R version (4.4.3) (R Core Team, 2025) with {lme4} package for multilevel modeling (Bates et al., 2015), the performance package for model diagnostics (Ludecke et al., 2021), and ggplot2 for visualization (Wickham, 2016).

4. Results

4.1 Descriptive Statistics and Model Assessment

Table 1 presents country-level summary statistics for ICT resources and school ICT environments across the 79 countries in our sample. Substantial variation exists both between and within countries, with OECD countries generally showing higher mean ICT resources (M = -0.04) compared to non-OECD countries (M = -0.72). Notable disparities in resource inequality (measured as the gap between the 90^{th} and 10^{th} percentiles of the ICTRES distribution) were observed, averaging 2.18 overall but slightly higher in non-OECD countries (M = 2.28) compared to OECD countries (M = 2.06).

Table 1. Country-level summary statistics of ICT resources and school ICT environment across OECD and non-OECD countries based on PISA 2018 data

Country	OECD	Country Mean_ICTRES	Country_Mean_ICTSCH	ICTRES_90th %	ICTRES_10th%	ICTRES_Inequality	N_schools	N_Students
Albania	0	-1.11	6.48	0.06	-2.31	2.37	327	6359
United Arab Emirates	0	0.39		1.87	-1.23	3.09	755	19277
Argentina	0	-0.87		0.33	-1.98	2.32	455	11975
Australia	1	0.59	7.53	1.87	-0.42	2.29	763	14273
Austria	1	0.08	6.03	1.02	-0.88	1.90	291	6802
Belgium	1	0.20	5.89	1.29	-0.88	2.17	288	8475
Bulgaria	0	-0.37	6.12	0.56	-1.42	1.97	197	5294
Bosnia and Herzegovina	0	-0.56		0.33	-1.43	1.76	213	6480
Belarus	0	-0.57		0.21	-1.46	1.67	234	5803
Brazil	0	-1.21	4.32	-0.13	-2.19	2.07	597	10691
Brunei Darussalam	0	-0.28	6.42	1.29	-1.78	3.08	55	6828
Canada	1	0.38		1.74	-0.88	2.62	821	22653
Switzerland	1	0.18	6.24	1.29	-0.88	2.17	228	5822
Chile	1	-0.63	5.45	0.69	-1.78	2.47	254	7621
Colombia	1	-1.35		0.14	-2.91	3.05	247	7522
Costa Rica	0	-0.98	5.38	0.18	-2.31	2.50	205	7221
Czech Republic	1	-0.09	5.57	0.77	-0.88	1.65	333	7019
Germany	1	0.03		1.02	-0.98	2.00	223	5451
Denmark	1	0.84	7.52	1.87	-0.15	2.02	348	7657
Dominican Republic	0	-1.47	4.18	-0.14	-2.86	2.72	235	5674
Spain	1	-0.08	6.05	0.97	-1.03	2.00	1089	35943
Estonia	1	0.02	6.47	0.77	-0.87	1.64	230	5316
Finland	1	0.15	7.19	1.02	-0.62	1.64	214	5649
France	1	-0.15	6.00	0.77	-1.42	2.19	252	6308
United Kingdom	1	0.50	7.12	1.87	-0.62	2.49	471	13818
Georgia	0	-0.84	5.28	0.10	-1.78	1.88	321	5572
Greece	1	-0.34	6.57	0.69	-1.34	2.03	242	6403
Hong Kong	0	-0.29	7.16	0.76	-1.23	1.99	152	6037
Croatia	0	-0.41	6.03	0.37	-1.23	1.60	183	6609
Hungary	1	-0.23	6.14	0.69	-1.23	1.92	238	5132
Indonesia	0	-1.93		-0.25	-2.91	2.66	397	12098
Ireland	1	0.09	6.15	1.29	-0.88	2.17	157	5577
Iceland	1	0.43	6.86	1.29	-0.39	1.69	142	3296
Israel	1	0.05	5.86	1.29	-1.12	2.41	174	6623
Italy	1	-0.24	5.72	0.69	-1.22	1.91	542	11785
Jordan	0	-0.93		0.34	-2.31	2.66	313	8963
Japan	1	-0.51	4.29	0.41	-1.44	1.85	183	6109
Kazakhstan	0	-0.86	6.90	0.18	-1.80	1.98	616	19507
Korea	1	-0.36	6.35	0.48	-1.23	1.71	188	6650
Kosovo	0	-0.76		0.25	-1.78	2.02	211	5058
Lebanon	0	-0.69		0.55	-1.98	2.53	313	5614
Lithuania	1	-0.23	6.92	0.63	-1.16	1.79	362	6885
Luxembourg	1	0.24	6.46	1.29	-0.88	2.18	44	5230
Latvia	1	-0.14	6.44	0.69	-1.06	1.75	308	5303
Macao	0	-0.23	6.37	0.69	-1.23	1.92	45	3775
Morocco	0	-1.57	4.09	-0.11	-2.91	2.80	179	6814
Moldova	0	-0.89		0.06	-1.91	1.97	236	5367
Mexico	1	-1.36	5.38	0.09	-2.56	2.66	286	7299
North Macedonia	0	-0.49		0.38	-1.47	1.85	117	5569
Malta	0	0.36	6.25	1.29	-0.62	1.92	50	3363
Montenegro	0	-0.48		0.48	-1.48	1.96	61	6666
Malaysia	0	-1.11		0.18	-2.31	2.49	191	6111
Netherlands	1	0.55		1.87	-0.36	2.23	156	4765
Norway	1	0.67		1.35	-0.34	1.69	251	5813
New Zealand	1	0.33	7.09	1.29	-0.87	2.16	192	6173
Panama	0	-1.32	5.18	0.14	-2.81	2.94	253	6270
Peru	0	-1.66		-0.11	-3.77	3.66	340	6086
Philippines	0	-1.64		-0.15	-2.91	2.76	187	7233
Poland	1	-0.17	5.64	0.69	-1.13	1.82	240	5625
Portugal	1	-0.25		0.69	-1.23	1.92	276	5932
Qatar	0	0.24		1.87	-1.23	3.09	188	13828
Baku-Azerbaijan	0	-0.94		0.09	-1.98	2.07	197	6827

Country	OECD	Country Mean_ICTRES	Country_Mean_ICTSCH	ICTRES_90th %	ICTRES_10th%	ICTRES_Inequality	N_schools	N_Students
B-S-J-S China	0	-0.58		0.69	-1.47	2.16	361	12058
Mosco Region-RUS	0	-0.12	7.23	0.91	-1.15	2.06	61	2016
Tatarstan-RUS	0	-0.43	7.26	0.37	-1.23	1.60	239	5816
Romania	0	-0.56		0.33	-1.50	1.84	170	5075
Russian Federation	0	-0.38	7.19	0.49	-1.23	1.72	263	7608
Saudi Arabia	0	-0.33		1.17	-1.77	2.95	234	6136
Singapore	0	0.11	6.78	1.29	-1.15	2.44	166	6676
Serbia	0	-0.59	5.41	0.21	-1.47	1.68	187	6609
Slovak Republic	1	-0.19	6.52	0.69	-1.16	1.85	376	5965
Slovenia	1	-0.02	5.72	0.69	-0.88	1.57	345	6401
Sweden	1	0.51	6.93	1.29	-0.57	1.87	223	5504
Chinese Taipei	0	-0.39	5.96	0.69	-1.48	2.17	192	7243
Thailand	0	-1.27	6.53	0.31	-2.27	2.59	290	8633
Turkey	1	-1.07	5.39	0.02	-2.31	2.33	186	6890
Ukraine	0	-0.63		0.21	-1.50	1.72	250	5998
Uruguay	0	-0.88	5.79	0.33	-2.14	2.47	189	5263
United States	1	0.20	7.15	1.29	-1.19	2.48	164	4838
Vietnam	0	-1.54		-0.35	-2.56	2.21	151	5377
Average	-	**-0.41**	**6.17**	**0.69**	**-1.49**	**2.18**	**273.79**	**7650.05**
Total	-	-	-	-	-	-	**21903**	**612004**
OECD Average	-	**-0.04**	**6.28**	**0.99**	**-1.07**	**2.06**	**306.14**	**7960.19**
OECD Total	-	-	-	-	-	-	**11327**	**294527**
Non-OECD Average	-	**-0.72**	**6.01**	**0.43**	**-1.85**	**2.28**	**245.95**	**7383.19**
Non-OECD Total	-	-	-	-	-	-	**10576**	**317477**

Note. ICT = Information and Communication Technology; OECD = Organization for Economic Co-operation and Development; ICTRES = ICT resources; ICTSCH = ICT resources at school; ICT inequality represents differences between 90th and 10th percentiles within countries

Table 2 presents descriptive statistics for the student-level and school-level ICT variables used in our analysis. The substantial sample size (N = 612,004 students) provides robust estimates across variables. The index of ICT availability at home (ICTHOME) had a mean of 7.52 (SD = 2.68), and the index of schools' ICT infrastructure (ICTSCH) had a mean of 6.01 (SD = 2.74), underscoring the variability.

Table 2. Descriptive Statistics and Pairwise Correlations for Study Variables

Variable	Mean (SD)	Minimum	Maximum	Pairwise Correlation Coefficients								
				OECD	ICTHOME	ICTSCH	ICTRES	HOMESCH	INTICT	COMPICT	ICTCLASS	READ
OECD	-	-	-	-								
ICTHOME	7.52 (2.68)	0	11	0.22	-							
ICTSCH	6.01 (2.74)	0	10	0.04	0.38	-						
ICTRES	-0.77 (1.27)	-4.095	4.007	0.29	0.54	0.22	-					
HOMESCH	0.103 (1.087)	-2.698	3.315	-0.11	0.15	0.19	0.09	-				
INTICT	0.004 (1.037)	-3.024	2.772	0.03	0.08	0.015	0.15	0.19	-			
COMPICT	-0.033 (1.004)	-2.619	2.578	0.03	0.13	0.06	0.16	0.22	0.52	-		
ICTCLASS	-0.063 (0.996)	-1.219	2.439	0.08	0.12	0.21	0.14	0.17	0.05	0.07	-	
READ	446.61 (110.698)	9.208	888.468	0.29	0.17	0.02	0.32	-0.11	0.17~	0.13	0.002	-

Note. Based on total sample size 612,004. SD = standard deviation; OECD = indicator for OECD membership; ICTHOME

= index of ICT availability at home; ICTSCH = index of schools' ICT infrastructure; ICTRES = ICT resources at school; HOMESCH = use of ICT for school-related tasks at home; INTICT = interest in ICT; COMPICT = perceived ICT competence; ICTCLASS = use of ICT in classroom; READ = students' reading achievement scores. All correlations were statistically significant at <.001 level except for the correlation between INTICT and READ (p = .29)

Table 2 presents descriptive statistics and correlation coefficients for the key ICT variables in our analysis. Notable correlations include positive associations between reading achievement and ICT resources (r = 0.32), but negative correlation with ICT use for school tasks at home (r = -0.11). OECD membership showed moderate correlation with home ICT availability (r = 0.22) and ICT resources (r = 0.29), reflecting technology access disparities between economically developed and developing countries. Figure 1 illustrates the distribution of standardized ICT factors across OECD and non-OECD countries. The boxplots reveal substantial variation in both the levels and distributions of technology indicators between economically developed and developing nations.

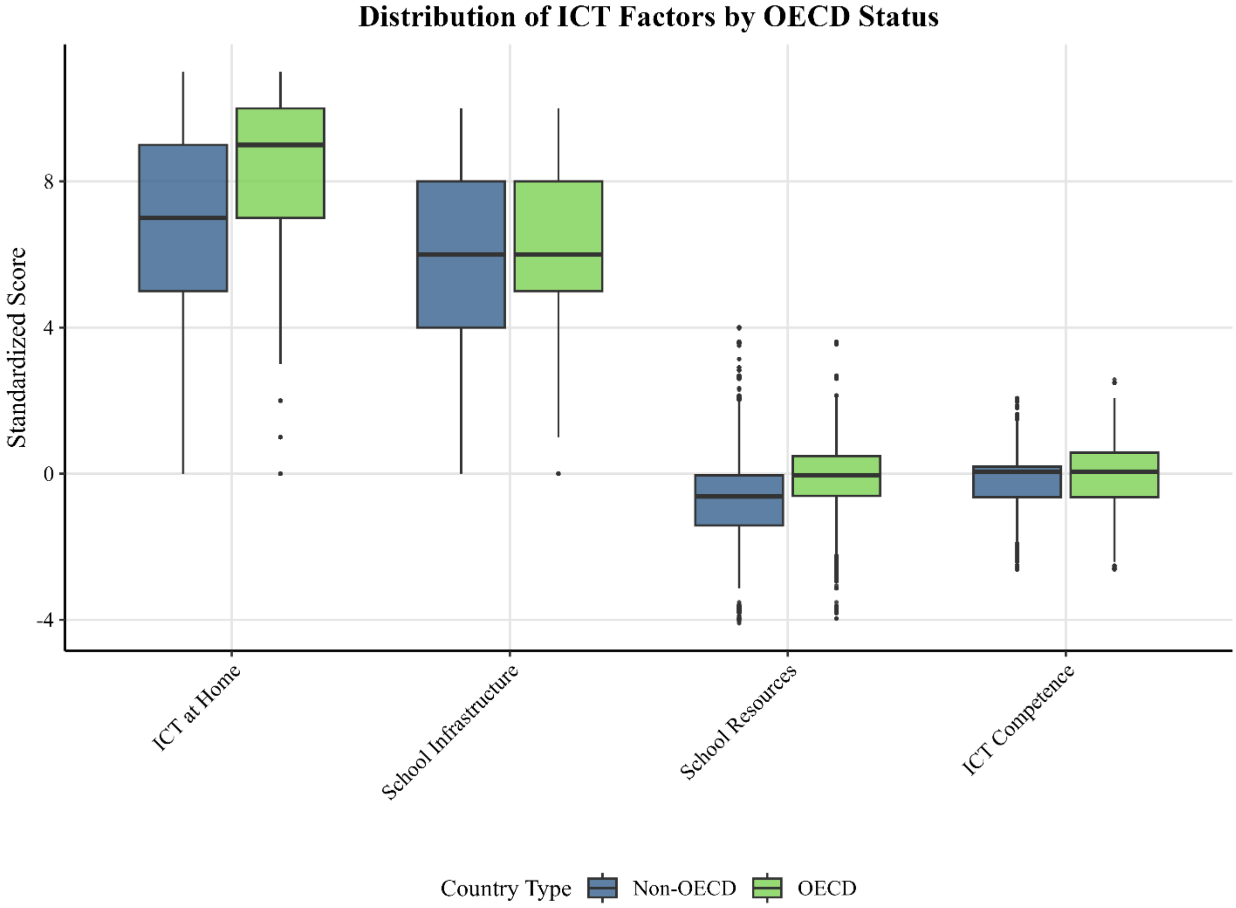

Figure 1. Distribution of standardized ICT factors across OECD and non-OECD countries

The boxplots show median values (horizontal lines), interquartile ranges (boxes), and outliers (points) for key technology indicators.

To establish a baseline for variance decomposition, we estimated a three-level null model with random intercepts for both countries and schools. This model revealed significant clustering at both levels, with an interclass correlation of 10.67% at the country level and 0.93% at the school level, as shown in Table 3. The overall fixed intercept was 450.66 (SE = 0.06, p < .001), representing the grand mean reading score across all observations when no predictors are included.

Model fit statistics presented in Table 3 demonstrate progressive improvement from the null model (AIC = 7,754,651) to the fixed-effects model (AIC = 3,701,076), random slopes model (AIC = 3,681,644), and cross-level interaction model (AIC = 3,697,622). This pattern confirms that incorporating ICT predictors and their interactions significantly improves model fit, supporting our analytical approach.

Table 3. Comparative Analysis of Parameter Estimates Across Hierarchical Linear Models

Parameters	Null Model	Fixed-Effect Model	Random Intercept, Random Slope Model	Cross-Level Interactions
Fixed Effects				
Intercept	450.66*** (0.06)	516.47*** (0.55)	519.24*** (0.61)	466.73*** (5.83)
ICTHOME	-	-2.98*** (0.08)	-3.32*** (0.09)	3.98*** (0.19)
COMPICT	-	4.28*** (0.18)	4.23*** (0.20)	3.83*** (0.29)
INTICT	-	8.43*** (0.16)	8.66*** (0.16)	7.98*** (0.24)
HOMESCH	-	-8.16*** (0.20)	- 8.73*** (0.12)	-8.25*** (0.26)
ICHSCH	-	-2.32*** (0.04)	-2.20*** (0.04)	6.86*** (0.20)
ICTRES	-	10.62*** (0.20)	12.18*** (0.20)	10.56*** (0.28)
ICTCLASS	-	-0.62** (0.17)	-1.79*** (0.07)	-0.41~ (0.25)
ICTHOME: ICTSCH	-	-	-	-1.20*** (0.02)
COMPICT: ICTRES	-	-	-	-1.03*** (0.19)
INTICT: ICTCLASS	-	-	-	0.42* (0.0.18)
Random Effects				
CNTSCHID (Intercept)	2748.35	2012.59	2038.23	1924.14
CNTRYID (Intercept)	31498.78	2277.62	255656.63	1652.59
Model Fit				
AIC	7,754,651	3,701,076	3,681,644	3,697,622
BIC	7,754,643	3,701,192	3,681,855	3,697,770
Country ICC	0.11	0.008	0.51	0.006
School ICC	0.009	0.007	0.004	0.007
Conditional R-squared	0.09	0.008	0.51	0.015
N-Student	606,627	288,489	288,489	288,489
N-School	21,752	13,509	13,509	13,509
N-Country	79	52	52	52

Note. Standard errors are presented in parentheses. ICC = intraclass correlation coefficient; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; ICTRES = ICT resources at school; HOMESCH = use of ICT for school-related tasks at home; INTICT = interest in ICT; COMPICT = perceived ICT competence; ICTCLASS = use of ICT in classroom

4.2 Research Question 1: Student-Level ICT Factors and Reading Achievement

Our analysis revealed complex relationships and sometimes counterintuitive relationships between student-level ICT factors and reading achievement, with coefficient patterns evolving meaningfully across model specifications. Looking at Table 3, we observe intriguing transition in ICT effects as we progress from simpler to more sophisticated models. Home ICT access (ICTHOME) demonstrates a remarkable sign reversal, shifting from significantly negative in the fixed-effects model (b = -2.98, p < .001) to strongly positive in the cross-level interaction model (b = 3.98, p < .001). This transition suggests that without accounting for cross-level interactions, we might substantially misunderstand how home technology relates to literacy development.

Students' perceived technology competence (COMPICT) and interest in ICT (INTICT) maintained consistent positive relationships across all model specifications, though with varying magnitudes. Interest in ICT showed the strongest and most stable positive association (raging from b = 7.98 to b = 8.66 across models), underscoring the importance of intrinsic motivation in technology-enhanced learning environments. Perceived competence, while still positive, showed more modest effects (approximately b = 4) across specifications.

Most notably, the use of ICT for school-related tasks at home (HOMESCH) demonstrated a consistently strong negative relationship with reading scores across all models (approximately b = -8.4, p < .001), a counterintuitive finding given educational policies promoting technology integration. This stable negative effect persisted even when accounting for complex cross-level interactions, suggesting fundamental concerns about how academic technology use at home might relate to reading development in the absence of appropriate guidance or structure.

4.3 Research Question 2: Country-Level ICT Resource Inequality and Reading Outcomes

The relationship between ICT resource distribution and reading achievement evolved substantially as we progressed from simpler to more complex model specifications. As shown in Table 3, country-level variance demonstrated a dramatic trajectory across our model sequence, initially accounting for 10.67% of total variance in the null model, then plummeting to just 0.60% of total variance in the cross-level interaction model. This striking reduction suggests that specific technology-related mechanisms, rather than undefined country characteristics, explain much of the cross-national variation in reading outcomes. As shown in Figure 2, countries cluster based on their mean ICT resources and school infrastructure, with circle size representing mean reading achievement. This visualization reveals how national technology profiles relate to overall literacy outcomes across global contexts.

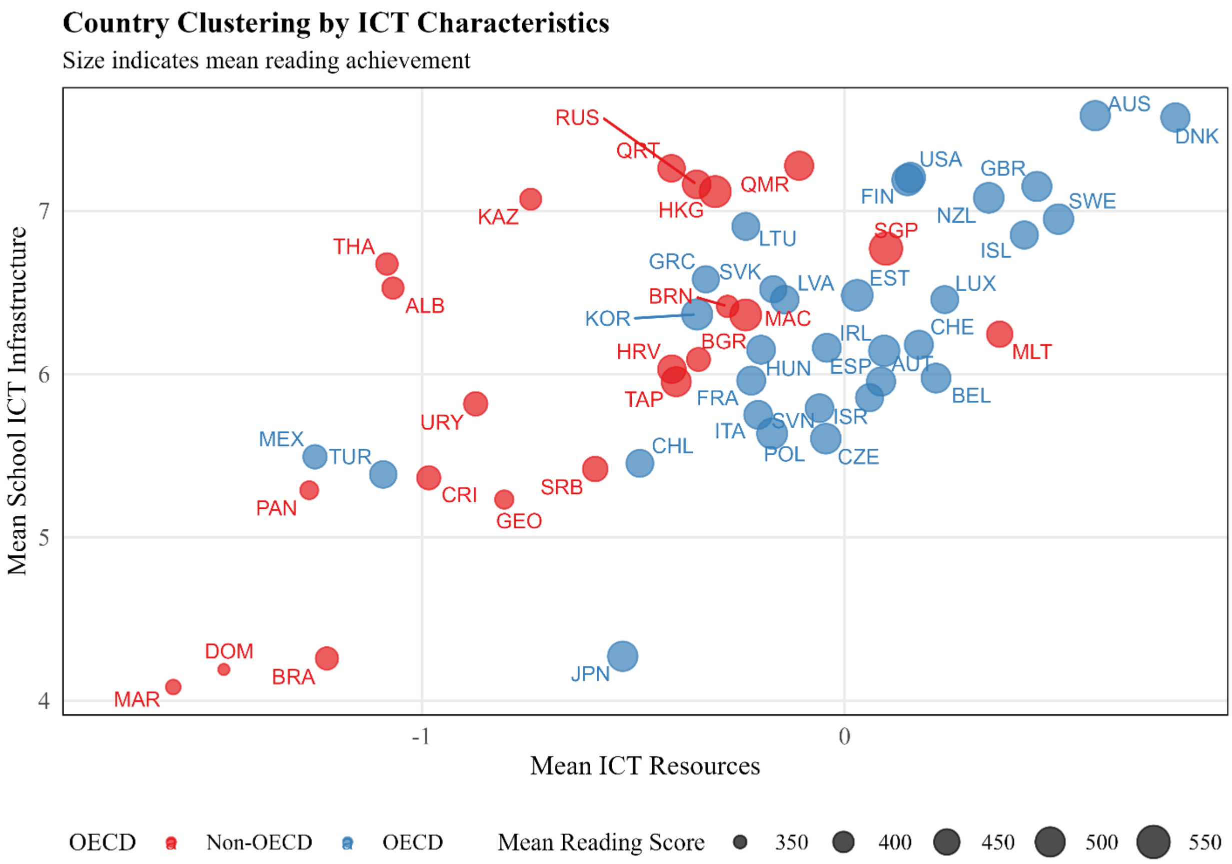

Figure 2. Country clustering based on mean ICT resources and school infrastructure

Circle size represents mean reading achievement, with larger circle indicating higher performance.

Figure 2 reveals how countries cluster according to their technology profiles, with higher-performing nations (larger circles) predominantly occupying the upper-right quadrant of high resources and infrastructure. However, Figure 3 introduces a critical nuance to this picture, showing that within country inequality in ICT resources correlates negatively with reading achievement ($r = 0.41$, $p < .001$), regardless of absolute circle levels. This pattern challenges simplistic "more is better" assumptions about educational technology and suggests that equitable distribution may matter more than raw quantity for system-wide outcomes. Figure 3 demonstrates the relationship between national ICT resource inequality and reading achievement. The scatter plot and trend line illustrate how within-country disparities in technology resources correlate with national reading outcomes, regardless of absolute resource levels.

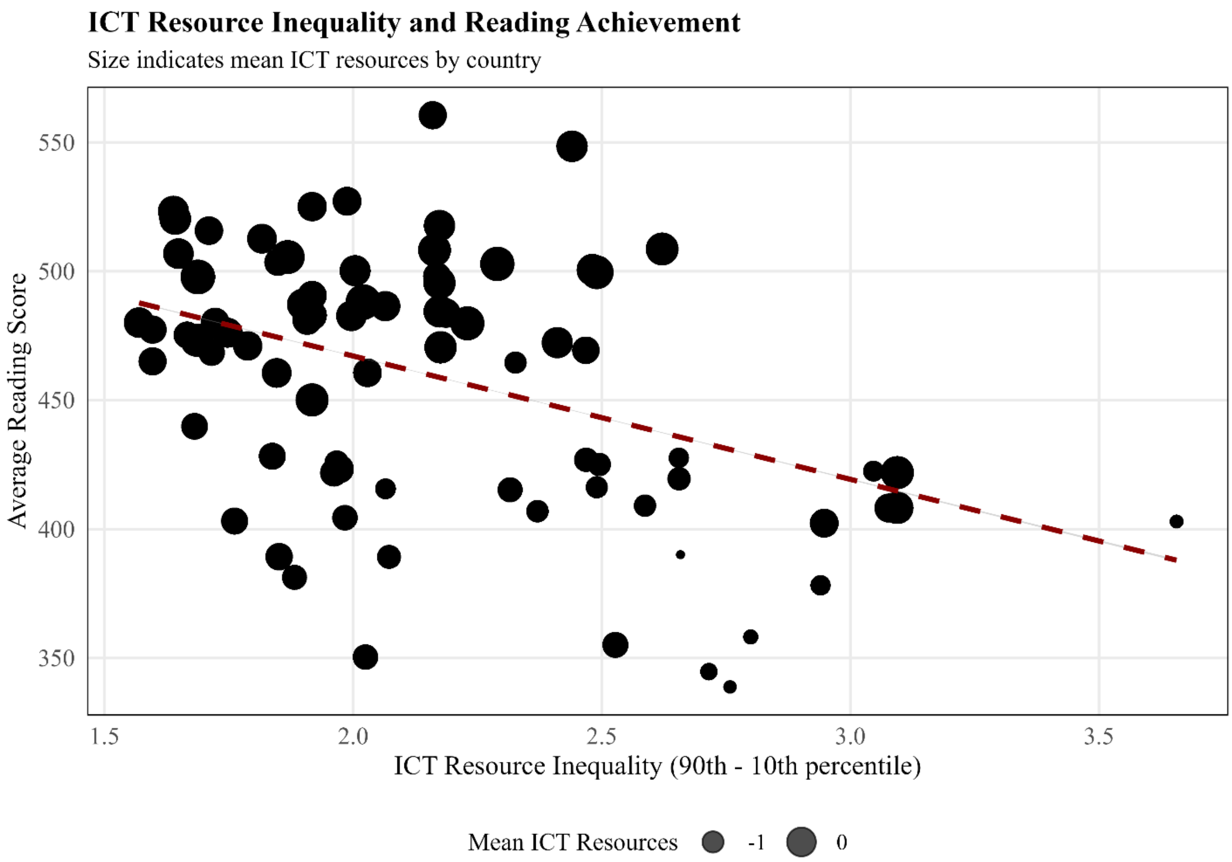

Figure 3. Relationship between national ICT resource inequality and reading achievement

ICT inequality is measured as the difference between 90th and 10th percentiles of standardized ICT resources within each country.

The country-level findings demonstrate the importance of examining both absolute resource levels and distributional patterns when considering technology's relationship with educational outcomes. The clustering patterns in Figure 2, combined with the substantial reduction in country-level variance across models, suggest that the national technology profiles represent complex configurations of resources rather than simple metrics.

4.4 Research Question 3: Cross-Level Interactions and Compensatory Effects

Our exploration of cross-level interactions revealed perhaps the most theoretically significant findings of the study, with interaction patterns evolving from implicit random effects to explicit compensatory mechanisms. The random slopes model demonstrated substantial school-level variation in how ICT factors relate to reading (Table 3), but the cross-level interaction model transformed these general patterns into specific mechanisms.

The interaction between home ICT access and school infrastructure emerged as particularly noteworthy (b = -1.20, p < .001), with the negative coefficient indicating a compensatory rather than amplifying pattern. Figure 4 illustrates this relationship, students in technology-poor schools (green line) show dramatically steeper positive slopes for home technology access compared to peers in technology-rich schools (blue line). This visualization demonstrates how school resources can potentially offset home disadvantages, a finding with substantial equity implications. Figure 4 visualizes the interaction effect between home ICT access and school ICT infrastructure on reading achievement scores. The differential slopes illustrate how the relationship between home technology access the reading outcomes varies substantially across different school technology environments.

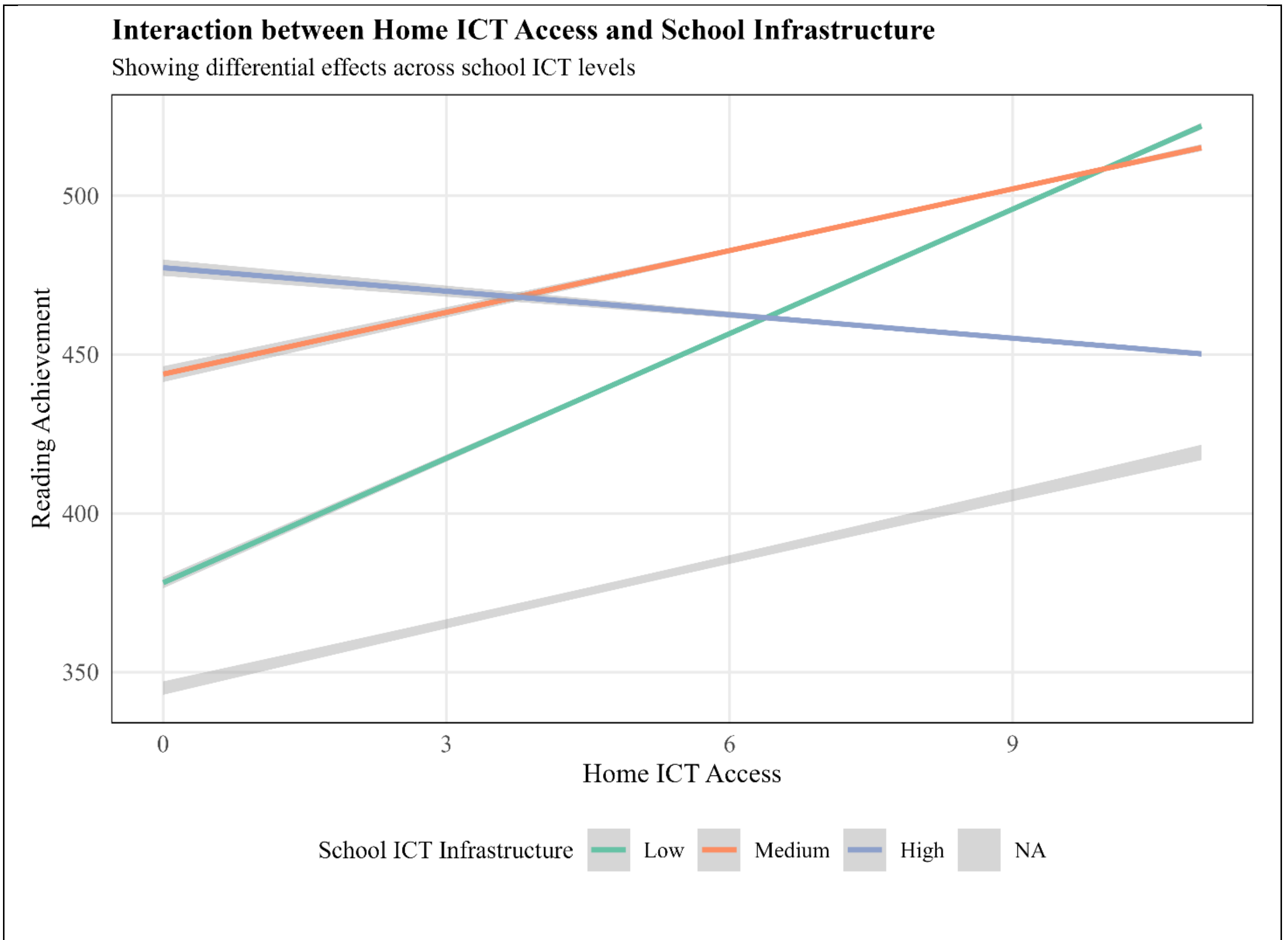

Figure 4. Interaction effect between home ICT access and school ICT infrastructure on reading achievement scores

Lines represent predicted reading scores at different levels of school infrastructure.

Note. Based on hierarchical linear model with cross-level interactions (b = -1.20, p < .001). NA refers to schools without available infrastructure data.

Similarly, the interaction between perceived ICT competence and school resources followed a compensatory pattern (b = -1.03, p < .001), suggesting that well-resourced schools may particularly benefit students with lower technological self-efficacy. In contrast, the positive interaction between interest and classroom integration (b = 0.42, p = .019) suggests that motivation and implementation can work synergistically, with technology-rich classrooms particularly benefiting already-interested students.

These varied interaction patterns emphasize that technology's relationship with learning occurs through specific mechanisms rather than uniform effects. The progression from random slopes to explicit interactions allows us to move beyond the question of whether effects vary to understand precisely how they vary, a critical distinction for both theory and practice.

5. Discussion

5.1 Student-Level ICT Factors and Reading Achievement

Our analysis revealed intricate relationships between student-level ICT factors and reading achievements that challenge simplistic narratives. Home ICT access (ICTHOME) demonstrated a remarkable sign reversal across model specifications, shifting from significantly negative in the fixed-effects model (b = -2.98, p < .001) to strongly positive in the cross-level interaction model (b = 3.98, p < .001). This transition aligns with Lee and Wu's (2012) finding that home technology access shows complex, contextually dependent relationships with reading outcomes. This sign reversal suggests that without accounting for cross-level, researchers might fundamentally misunderstand how home technology relates to literacy development, potentially explaining inconsistencies in previous findings by Biagi & Loi (2013) and Bhutoria and Aljabri (2022).

Students' perceived competence with technology and interest in ICT maintained consistently positive relationships with reading achievements across all model specifications. Interest in ICT showed particularly strong positive associations (ranging from $b = 7.98$ to $b = 8.66$), reinforcing findings by Rohatgi et al. (2016) and Aesaert et al. (2017) regarding the importance of technological self-efficacy. Similarly, the strong positive effect of interest supports Kunia-Habenicht and Goldhammer's (2020) conceptualization of ICT engagement as multifaceted, encompassing not just usage but also attitudinal dimensions. This pattern mirrors Li and Petersen's (2022) finding that intrinsic motivation often drives effective technology use more powerfully than external factors.

Perhaps most notably, using ICT for school-related tasks at home demonstrated a consistently stronger negative relationship with reading scores, a counterintuitive finding echoes Gomez-Fernandes and Mediavilla's (2021) observation that academic application of technology frequently shows negative relationships with performance. Similarly, our results align with Steffens' (2014) caution against high-frequency ICT use without appropriate guidance. The persistence of this negative effect even when accounting for complex cross-level interactions reinforces concerns raised by both Gubbels et al. (2020) and Huang et al. (2021) about potential negative consequences of unstructured academic technology use, suggesting fundamental issues with current approaches to technology-based homework.

5.2 Country-Level ICT Resource Inequality and Reading Outcomes

Our examination of country-level technology patterns revealed compelling evidence regarding the importance of resource distribution, not just absolute levels. The dramatic trajectory of country-level variance across our model sequence, from initially accounting for 10.67% of total variance in the null model to just 0.60% in the cross-level interaction model, suggests that specific technology-related mechanisms explain much of the cross-national variation in reading outcomes, rather than undefined country characters. This finding extends Lafontaine et al.'s (2015) work on cross-national opportunity-to-learn disparities by identifying specific technological factors that contribute to these differences.

The country clustering analysis (Figure 2) initially appears to support conventional wisdom, with high-performing countries predominantly occupying the upper-right quadrant of high resources and infrastructures. However, Figure 3 introduces a critical nuance, revealing that within-country inequality in ICT resources correlates negatively with reading achievement ($r = -0.41$, $p < .001$), regardless of absolute resource levels. This pattern supports Zhang and Liu's (2016) finding that cultural capital and resource distribution often matter more than raw technology access, while also aligning with education production function perspectives that incorporate distributional concerns (Agasisti et al., 2023; Hanushek, 2020).

The variance decomposition across models suggests that educational technology operates through specific, quantifiable mechanisms rather than through generalized country effects. These patterns align with Meng et al.'s (2019) cross-cultural comparison of China and Germany, which found that ICT effects are substantially moderated by national educational contexts. Our findings on resource inequality further support Warschauer and Matuchniak's (2010) argument that the "quality of use" divides often supersede basic access divides in determining educational outcomes.

5.3 Cross-Level Interactions and Compensatory Effects

Our exploration of cross-level interactions revealed perhaps the most theoretically significant findings of the study. The interaction between home ICT access and school infrastructure ($b = -1.20$, $p < .001$) demonstrated a compensatory rather than amplifying pattern. As illustrated in Figure 4, students in technology-poor schools show dramatically steeper positive slopes for home technology access compared to peers in technology-rich schools. This visualization empirically extends Camerini et al.'s (2018) theoretical framework regarding compensatory digital resources, while challenging Reich's (2020) concerns about amplification effects where technology disproportionately benefits already-advantaged students.

Similarly, the interaction between ICT competence and school resources ($b = -1.20$, $p < .001$) followed a compensatory pattern, suggesting that students with lower technological self-efficacy may particularly benefit from well-resourced school environments. This finding adds layers to Rohatgi et al.'s (2016) work on ICT self-efficacy by demonstrating how institutional contexts can moderate individual-level effects. The compensatory pattern we observed contrasts with Zheng et al.'s (2022) concern that technology might widen existing achievement gaps, suggesting instead that strategic resource allocation could potentially narrow rather than widen these disparities.

The positive interaction between interest and classroom integration ($b = 0.42$, $p = .019$) provides a complementary perspective, indicating that motivation and implementation can work synergistically. This finding builds on Petko et al.'s (2017) emphasis on perceived quality of educational technology and supports Tondeur et al.'s (2020) sociotechnical systems framework, where technological and social factors mutually reinforce each other. The positive interaction further aligns with Kong et al.'s (2022) finding that affective dimensions significantly mediate technology's impact on reading outcomes in digital context.

These varied interaction patterns demonstrate that technology's relationship with learning occurs through specific mechanisms rather than uniform effects. Our findings move beyond Erdogdu and Erdogdu's (2015) examination of contextual factors by quantifying precise cross-level interactions, providing concrete evidence for what Lezhnia and Kismihok (2022) described as the fundamentally context-dependent nature of educational technology effects.

6. Conclusion and Implications

This study advances our understanding of ICT's complex relationship with reading achievement by exploring contextual factors, distributional patterns, and cross level interactions. Our findings provide empirical support for viewing digital divides as multidimensional and context-dependent rather than binary phenomena. The compensatory relationship between home and school technology amplifies existing inequalities and offers promising avenues for addressing educational disparities through strategic resource allocation.

The negative correlation between ICT resource inequality and reading achievement highlights that equitable distribution may be more important than absolute resource levels for system-wide literacy outcomes. This pattern, alongside our finding that interest and perceived competence consistently relate positively to achievement, suggests that educational technology policies should prioritize both distributional equity and student engagement rather than focusing exclusively on expanding access.

6.1 Theoretical Implications

Our findings support viewing digital divides as multidimensional and context-dependent rather than binary. The compensatory relationship between home and school technology extends frameworks that conceptualize digital divides as operating across multiple levels (van Dijk, 2020).

The negative correlation between ICT resource inequality and reading achievement supports production function approaches that incorporate distributional concerns (Agasisti et al., 2023), suggesting that like other educational inputs, technology resources may yield diminishing returns past certain thresholds (Ghimire & Mokhtari, 2024), with equity in distribution potentially more important than absolute levels for system-wide outcomes.

6.2 Pedagogical Implications

Our findings underscore the importance of context-specific technology integration. In resource-limited schools, structured methods like device rotation or extended computer lab hours could mitigate home-school disparities, while better-equipped schools might focus be on enhancing critical digital literacy skills rather than maximizing exposure (Buckingham, 2021). Teachers should consider providing structured guidance for technology-related homework, as unstructured home technology use may correlate negatively with students reading performance (Zheng et al., 2022). The positive correlations between ICT interest, confidence, and reading achievement suggest exploring pedagogical strategies that cultivate digital engagement through authentic tasks (Ito et al., 2018) and gradually increasing technological challenges (Dexter & Richardson, 2019).

6.3 Policy Implications

The compensatory relationship between home and school ICT access suggests that technology provision should be strategically targeted rather than uniformly distributed. In contexts with limited home access, school-based provision becomes especially critical, while areas with widespread home access might better focus on integration quality. The negative relationship between resource inequality and reading achievement suggests that policies aimed at reducing within system disparities may yield greater benefits than simply increasing average resource levels.

Finally, our country clustering analysis revealed distinct technology profiles that transcend simple economic categorizations, suggesting context-aligned investments may be more effective than adopting standardized approaches based on international benchmarking alone.

7. Limitations and Future Research

While this study provides valuable insights into multilevel relationships between ICT factors and reading achievement, several important limitations must be acknowledged.

7.1 Methodological Constraints

The cross-sectional nature of PISA data prevents establishing causal relationships between ICT variables and reading achievement. Associations identified should be interpreted as correlational rather than causal, as unobserved variables may influence both ICT and patterns and reading outcomes. Longitudinal studies tracking both technology use and reading development over time would provide stronger evidence for causal mechanisms (Camerini et al., 2018).

Our analysis relies primarily on self-reported measures of technology access, attitudes, and usage patterns. Despite PISA's rigorous validation procedures, self-report data remains susceptible to social desirability bias, recall errors, and varying interpretations of scale points across cultural contexts (Rutkowski & Svetina, 2014).

Despite PISA's comprehensive sampling approach, our analytical sample includes only 47.1% of the original student sample and 65% of participating countries due to missing data on key ICT variables. While sensitivity analyses suggested minimal bias from these exclusions, the possibility remains that relationships might differ in excluded contexts. Methodological approaches that more robustly handle missing data, such as multiple imputation techniques specifically designed for multilevel structures, could address this limitation (Grund et al., 2018).

7.2 Conceptual and Measurement Limitation

The ICT measures available in PISA, while comprehensive relative to other international assessments, capture only certain dimensions of the complex technology ecosystem surrounding students. Notably absent are the measures of technological content quality, pedagogical approaches to technology integration, and specific digital reading activities. The items do not fully capture emerging technologies like artificial intelligence tools, mobile learning applications, or immersive technologies that may increasingly influence reading practices (Leu et al., 2019).

Additionally, the PISA reading assessment does not fully differentiate between traditional and digital reading skills. As reading increasingly occurs in digital environments with distinct comprehension demands, future research should employ more nuanced outcome measures that distinguish between various dimensions of digital reading proficiency (Coiro, 2020).

Our measures of ICT resource inequality (90^{th}-10^{th} percentile gap) provide useful but simplified metric of distributional patterns. More sophisticated inequality measures, such as Gini coefficients or Theil indices, might capture more nuanced aspects of technology distribution within educational systems (van Deursen & Helsper, 2018).

7.3 Contextual Limitations

While PISA 2018 represents the most recent cycle with comprehensive ICT measures available at the time of analysis, technological landscapes evolve rapidly. The COVID-19 pandemic likely accelerated and transformed patterns of educational technology use in ways not captured by our pre-pandemic data. Replication with PISA 2022 data, which includes post-pandemic measures, would provide important insights into how these relationships may have shifted.

Furthermore, our global analysis necessarily abstracts away from specific national and local contexts that may significantly moderate the relationships we identified. While our multilevel models account for clustering, they cannot fully capture the complex historical, cultural, and policy contexts that shape technology integration into different educational systems. Country-specific analyses or comparative case studies would complement our global approach by providing more contextualized understanding of these relationships (Xu & Soland, 2024).

Finally, our analysis focuses specifically on reading achievement, which represents only one dimension of educational outcomes. Technology's relationship with other cognitive skills, socio-emotional development, digital citizenship, and long-term educational trajectories may differ substantially from the patterns we observed for reading (Hershkovitz & Karni, 2018).

7.4 Future Research

These limitations suggest several promising directions for future research. Longitudinal studies tracking the co-evolution of technology access, use patterns, and reading development would provide stronger evidence regarding causal pathways and developmental trajectories. Mixed method approaches combining large-scale assessment data with qualitative case studies could illuminate the mechanisms underlying the statistical relationships we identified.

Research examining how the relationships between ICT factors and reading achievement vary across different student subgroups (beyond our country-level analysis) would provide important insights into potential equity implications. Similarly, studies examining how national and school policies moderate these relationships could offer more directly actionable guidance for educational leaders.

The compensatory relationship we identified between home and school ICT resources merits particular attention in future research. Experimental or quasi-experimental studies manipulating the balance of home and school technology provision could test the causal nature of this relationship and inform more targeted resource allocation strategies.

Finally, as artificial intelligence and other emerging technologies transform both the tools available to students and the nature of reading itself, continued research will be essential to understand how these technologies shifts influence literacy development in an increasingly digital world.

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Authors contributions

Dr. Nirmal Ghimire contributed to data modeling, analyses, writing, and visualization tasks. Mrs. Sushila Regmi contributed to the conception of the paper, collection of relevant articles for the literature review section, writing, proofreading, and revising the manuscript. Both authors read and approved the final manuscript.

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Competing interests

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

Informed consent

This study utilized publicly available secondary data from the OECD PISA 2018 dataset. Informed consent for the original data collection was obtained by the OECD from all participants according to their established protocols and ethical guidelines for the PISA assessment.

Ethics approval

The Publication Ethics Committee of the Redfame Publishing.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

Data availability statement

The PISA data collected from the 2018 cycle can be accessed through the OECD international database.

Organization for Economic Co-operation and Development (OECD). (2019). PISA 2018 dataset. Programme for International Student Assessment. https://www.oecd.org/pisa/data/2018database/

Data sharing statement

All data used in this study are publicly available from the OECD PISA 2018 database as referenced in the Data Availability Statement. No additional unpublished data were generated or analyzed during the current study.

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