Learning and Individual Differences 118 (2025) 102623

Contents lists available at ScienceDirect

Learning and Individual Differences

journal homepage: www.elsevier.com/locate/lindif

When struggling readers meet the screen – A secondary analysis of ePIRLS 2016 data

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ARTICLE INFO

Keywords:
Struggling readers
Digital reading comprehension
Large-scale assessments
Digital device usage
Academic digital reading activities

ABSTRACT

Despite past efforts to investigate how students' interactions with digital devices shape their digital reading comprehension skills, we still need more knowledge about struggling readers in digital reading contexts. Previous research has shown that digital reading comprehension is negatively associated with general digital device usage and positively associated with some academic digital reading activities in the general student population. We used data from ePIRLS 2016 to investigate whether such patterns are related differently to struggling and nonstruggling readers. For struggling readers, we found that digital reading comprehension was negatively associated with the general use of digital devices for schoolwork. There was no statistically significant relationship between academic digital reading activities and digital reading comprehension. In contrast, this relationship was positively associated with digital reading comprehension among nonstruggling readers. We discuss how typical digital classroom activities may be differently related to digital reading comprehension depending on students' print reading comprehension skills.

Educational relevance and implications

While digital reading comprehension strongly resembles traditional print reading comprehension, there are still features that are uniquely related to digital reading, such as navigating webpages to find relevant and credible information sources. These features may pose additional challenges for struggling readers' comprehension. Our study revealed that the time spent on digital devices for schoolwork was negatively associated with comprehension in this group of readers. Our findings have theoretical relevance for studies focusing on digital reading activities for struggling readers and could serve as a basis for more focused studies examining these relationships.

Before the COVID-19 pandemic, classrooms, at least in the Western world, had become highly digitalized. Hence, digital devices have become ubiquitous and indispensable in a wide range of student learning activities (Haleem et al., 2022). There are several benefits of technology-rich classrooms, such as the use of assistive technology for spell-checking and text-to-speech (Maor et al., 2016), but there are also challenges. For example, students may be distracted from learning activities by the nonacademic use of digital devices (Bergdahl et al., 2018; Kirkpatrick et al., 2017). Struggles with efficient reading on digital devices (e.g., tablets or laptops) are a problem that most students occasionally encounter, but some students have persistent difficulties with reading comprehension regardless of the medium (i.e., print or digital).

In this study, we utilized a unique dataset that allowed us to identify students who struggle with print-based reading (i.e., scoring within the lowest benchmark on a standardized reading test) and to explore these students' digital reading comprehension compared with that of their nonstruggling peers. More specifically, the aim of this study was to investigate how the use of digital devices both inside and outside the classroom was related to struggling readers' digital reading comprehension, as measured in the international large-scale assessment ePIRLS 2016. We chose this dataset because participation in PIRLS was a prerequisite for participating in ePIRLS in 2016, which enabled us to control for print reading comprehension when examining the same students' digital reading comprehension. Before presenting the research design of the present study, we introduce existing research on digital reading, struggling readers' digital reading comprehension and an outline of the ePIRLS assessment as follows.

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https://doi.org/10.1016/j.lindif.2024.102623
Received 29 February 2024; Received in revised form 7 November 2024; Accepted 20 December 2024
Available online 30 December 2024
1041-6080/

1. Digital reading comprehension activities

Although digital reading has been extensively studied for decades, there is still no clear consensus regarding its definition. Rapid technological developments have led to new types of digital texts, devices, and reading activities. To clarify existing definitions, Coiro (2021) proposed a framework that emphasizes the need to consider the characteristics of the reader, text, activity, and context as sources of influence for digital reading comprehension. In our study, we considered digital reading comprehension as the processing of webpages in an Internet environment, which includes uniquely distinct activities from print-based reading, such as navigation, integration, and evaluation of digital texts (Salmerón et al., 2018). While traditional literacy training in schools still has a role in nurturing students' skills, schools are increasingly introducing new academic tasks to model strategic digital reading and ultimately foster students' performance in digital domains. Nevertheless, for most, effectively managing the bulk of information available in digital systems such as the Internet remains a challenge.

Alexander (2020) argued that the current saturation of information negatively shapes the way students perceive digital reading and that students' perceptions of what it means to interact with digital texts may shift from knowledge building to information management. To counter such challenges, Alexander (2020) proposed that teachers should move away from overemphasizing digital reading activities involving simple search tasks. Instead, students should be given opportunities to interact and collaborate with meaningful digital reading activities, such as preparing for reading projects. These activities could increase students' motivation to engage in the task, placing greater personal value and emotional investment on the content and the abilities practiced. Secondary analyses of large-scale reading assessments of primary and middle school students have indicated that different digital reading activities are related in different ways to reading comprehension (Gilleece & Eivers, 2018; Mullis et al., 2017; Salmerón et al., 2023). In their reanalysis of the National Assessment of Educational Progress (NAEP) 2017 data, Salmerón et al. (2023) reported that the mere frequency of using digital devices for drill-and-practice activities in the reading classroom was negatively associated with reading comprehension among US fourth- and eighth-grade students. In contrast, meaningful academic digital reading activities, such as preparing reading projects and presentations, were positively associated with students' reading comprehension.

Notably, the NAEP 2017 assessment included only PDF-like digital texts, whereas other large-scale assessments, such as ePIRLS 2016, provide students with the opportunity to interact with internet-like environments. Gilleece and Eivers (2018) investigated the association between digital reading activities and digital reading comprehension in the ePIRLS 2016 assessment for Irish 4th-grade students. They reported that students who spent 30 min or more preparing reports and presentations with a computer in school scored approximately one-seventh of a standard deviation higher on ePIRLS than students who did not spend any time on this type of activity. In addition, more frequent use of computers for schoolwork at both home and school was associated with lower ePIRLS achievement scores.

Importantly, the reviewed studies did not differentiate between struggling and nonstruggling readers. Hence, the question of whether the relationship between academic digital reading activities and digital reading comprehension may be dependent on students' initial reading skills remains to be addressed.

1.1. Struggling readers and digital media

Although struggling readers have been researched for decades, the definition seems to be wide and heterogeneous (Arfé et al., 2018; Cain & Oakhill, 2006). Struggling readers have often been defined as the bottom performers on reading comprehension tests (Kanniainen et al., 2022; McMaster et al., 2014). Existing theoretical models of reading comprehension tend to focus on different aspects of the comprehension process (McNamara & Magliano, 2009). In this study, we have chosen the reading systems framework (RSF) (Stafura & Perfetti, 2017), a comprehensive theoretical foundation to explain why differences in reading comprehension arise. According to RSF, efficient reading comprehension occurs via a complex set of interconnected skills related to language processing at several levels of complexity ranging from word processing to discourse processing (Perfetti & Stafura, 2014). RSF assumes that reading comprehension is dependent on both foundational skills (e.g., orthographic knowledge, vocabulary, lexical knowledge, decoding and morphology) and comprehension models, which emphasize strategies and processes required to build a mental model of the situation described in the text (Kintsch, 1998; Van den Broek et al., 1999).

Feller et al. (2024) argue that RSF can be a useful theoretical framework to explain how and why students differ in their level of reading comprehension because it addresses higher- and lower-level processes and strategies related to reading comprehension. One way to illustrate this is to consider how a reader's lexical knowledge allows him or her to draw inferences from a text. Reading unfamiliar words taxes working memory, which in turn reduces the reader's ability to draw inferences from a text. Therefore, according to the RSF, struggling readers may achieve lower reading comprehension because they have poorer foundational reading skills (i.e., vocabulary, orthographic knowledge, and decoding skills), which allocates less cognitive capacity to comprehend texts at more complex levels (Feller et al., 2024). Hahnel et al. (2017) examined the relationship between working memory (i.e., memory updating) and digital reading comprehension, and they discovered differential effects on the relationship between working memory and digital reading comprehension for different reading tasks. These findings suggest that efficient working memory functions such as memory updating when reading hypertexts play an important role in digital reading comprehension. One could argue that reduced working memory capacity would then be associated with poorer digital reading comprehension for struggling readers, potentially due to having less free capacity to update working memory. The processing demands involved in digital reading might be more profound in struggling readers than in their nonstruggling peers because of the increased self-regulation imposed by the interactive characteristics of digital texts (Andresen et al., 2019; Anmarkrud et al., 2018). For example, struggling readers have been found to be more distracted from engaging in academic tasks by nonacademic use of digital devices, potentially contributing to poorer academic achievement (e.g., Bergdahl et al., 2018; Kirkpatrick et al., 2017; Sanders et al., 2023; Wu et al., 2018). Other studies have shown that readers with low reading comprehension scores spend more time on task-irrelevant activities, such as reading more task-irrelevant paragraphs (Hautala et al., 2022) or seeking task-relevant webpages (Naumann, 2015), when working with digital texts.

Despite an increased number of studies examining digital reading among struggling readers, this group has not been investigated to the same extent as nonstruggling readers in the vast literature on digital reading (Anmarkrud et al., 2018; Cavalli et al., 2019). This gap in the literature is particularly prominent in large-scale studies with representative samples, such as ePIRLS.

Reading comprehension scores on the PIRLS and ePIRLS are classified into four levels that are indicative of the international benchmark each student achieved. These international benchmarks are referred to as “low”, “intermediate”, “high” and “advanced” (see Mullis et al., 2017). From the lens of large-scale assessments, struggling readers can be defined as students obtaining a low international benchmark. These students can locate and retrieve superficial and explicit information in texts and graphics, draw simple inferences from texts, and interpret the central ideas and events in the text. In contrast, students who obtain the intermediate international benchmark can locate and reproduce several pieces of information from a text, draw straightforward inferences based on textual information and not prior knowledge, and show initial signs of a growing ability to interpret and integrate information from texts. In addition, students who obtain the highest international benchmark (i.e., advanced international benchmark) can distinguish, interpret, and infer complex information in texts and graphics; integrate information within and between texts; and begin evaluating the author's point of view via textual and visual elements.

In response to the challenges associated with struggling readers' digital reading comprehension, a potential solution could be that teachers scaffold struggling readers with specific academic digital reading activities (Alexander, 2020). Specifically, meaningful digital reading activities, such as reading projects (e.g., a school assignment where the students are asked to read about a particular topic for a presentation, debate, or report), can provide students with a sense of purpose, potentially supporting struggling readers in their digital tasks (Alexander, 2020). Although the importance of such digital reading activities for struggling readers has been emphasized in the literature (e.g., Kanniainen et al., 2019), to the best of our knowledge, this claim requires more empirical evidence. The aim of our study was to fill this gap.

1.2. The present study

The aim of this study was to investigate how struggling readers' digital reading activities inside and outside school relate to their digital reading achievements, as measured in ePIRLS. We chose this dataset because participation in PIRLS was a prerequisite for participating in ePIRLS 2016; thus, this dataset is highly valuable for the purpose of our study because it provides a unique opportunity to use print reading comprehension scores to classify struggling readers when examining the same students' digital reading performance. In this study, we sought answers to the following research questions:

RQ1. Does the frequency of the general use of digital devices for schoolwork relate to digital reading comprehension differently between struggling and nonstruggling readers?

RQ2. Does the frequency of meaningful academic digital reading activities involving digital devices relate differently to digital reading comprehension between struggling and nonstruggling readers?

With respect to RQ1, previous findings (Bergdahl et al., 2018; Salmerón et al., 2023) suggest that we can anticipate a negative association between the frequency of digital device use and digital reading comprehension. We expect that this relationship will be more negative among struggling readers than among other groups of readers because of the lower self-regulation ability of the former to cope with the interactive features of digital texts (Bergdahl et al., 2018; Kirkpatrick et al., 2017; Sanders et al., 2023; Wu et al., 2018). With respect to RQ2, previous findings (Mullis et al., 2017; Salmerón et al., 2023) indicate that meaningful academic digital reading activities are positively associated with digital reading comprehension. Given the relatively limited body of literature addressing this issue for struggling readers, we do not have any clear expectations about whether this relationship would be positively related to struggling readers than to their nonstruggling peers.

There is no difference in the fundamental reading processes when students read on paper and screen. Words must still be recognized, and meaning must be constructed from the word level, via sentences and paragraphs, up to situation models comprising the meaning of the text (e.g., Kintsch, 1998). Hence, researchers have expressed concerns for an "… arbitrary and binary distinction between 'old' and 'new' forms of reading" (Cho et al., 2018, p. 135), and established models of reading comprehension are considered relevant for digital reading (e.g., Salmerón et al., 2018). Consequently, to ensure that the potential effects of confounding variables do not influence the findings of our analyses, our study incorporated a comprehensive set of background characteristics that have been found to be associated with students' print reading comprehension. These factors include gender (e.g., Kanniainen et al., 2019), language use at home (e.g., Dalton et al., 2011), leisure reading frequency (e.g., Mol & Bus, 2011), socioeconomic status (SES) (e.g., Frønes et al., 2020) and self-concept (e.g., Conradi et al., 2014).

2. Methods

2.1. Participants

In 2016, 14 countries, 3033 schools and 85,463 fifth-grade students (49.68 % girls, mean age = 10.8) participated in both PIRLS and ePIRLS. The countries that participated were the UAE, Canada, China (Taipei), Denmark, Georgia, Ireland, Israel, Italy, Norway, Portugal, Singapore, Slovenia, Sweden, and the USA. The dataset contains an ordinal variable that indicates the international benchmark each student achieved on the PIRLS assessment (i.e., print reading comprehension). Students' print reading comprehension scores can be categorized into four different categories: (1) low international benchmark (i.e., $\leq$ 475 scale points), (2) intermediate international benchmark (i.e., 475–549 scale points), (3) high international benchmark (i.e., 550–624 scale points) and (4) advanced international benchmark (i.e., $\geq$ 625 scale points).

We used the benchmarks for PIRLS scores to define struggling readers as those who achieved a low international benchmark score (n = 14,495, 44.63 % girls). This approach allows us to test for moderation effects in regard to differences in the effects of print reading comprehension level and digital device practices on digital reading comprehension. Notably, the dataset does not include any information about why a particular participant is struggling with reading (i.e., a low international benchmark), and the struggling reader group probably contains both garden-variety poor readers and children with specific reading and learning disabilities. The manual for PIRLS and ePIRLS 2016 states that dyslexia or other learning disabilities should not be used as the sole reason for exclusion from the assessment. Instead, students with learning disabilities such as dyslexia should receive the necessary adaptations, making it possible to participate in the assessment (LaRoche & Foy, 2017).

2.2. Reading comprehension measures – PIRLS and ePIRLS

PIRLS is an international large-scale educational assessment that gauges trends in reading achievement for 10-year-old students in 4th or 5th grade (Mullis & Martin, 2015), a crucial transition stage in school—namely, the stage where students transition from learning how to read to reading for learning (Vacca et al., 1987). PIRLS is intended to assess students' reading comprehension when they are tasked with reading expository and narrative texts. Moreover, the PIRLS consists of items assessing four types of reading comprehension processes: (1) retrieving explicitly stated information, (2) drawing straightforward inferences, (3) interpreting and integrating information and ideas from passages, and (4) evaluating and criticizing content and textual elements (Mullis & Martin, 2015). In 2016, ePIRLS was introduced to assess digital reading comprehension specifically. In ePIRLS, participants navigate through an internet-like digital reading context with features such as hyperlinks, tabs, and pop-ups, containing expository texts about various academically related topics within science and social science. In ePIRLS, the items assess the same four types of reading comprehension processes as in PIRLS. In this study, the overall ePIRLS score was used as a measure of participants' digital reading comprehension.

Like other large-scale educational assessments, ePIRLS achievement scores are estimated via plausible values (LaRoche et al., 2015). Since each student completes only two texts in the ePIRLS, a multiple imputation of plausible values represents what the achievement score would have been if each student had completed every item in each assessment. As mentioned, plausible values are imputed values and should therefore not be interpreted as test scores for the students who participated in the assessment. These values are estimated as five random draws from an empirically derived distribution of scores from the students' observed responses on the reading passages they completed as well as their responses from background variables. Individual usage of plausible values provides biased estimates of individual students' reading comprehension. However, when they are grouped together (i.e., all five plausible values are used in statistical modeling), they provide unbiased estimates of population characteristics (Martin et al., 2017; Wu, 2005). To make the reading achievement scores comparable, the scores are calibrated with item response theory (IRT) models to place students' achievement scores on the same scale as the item characteristics for the items belonging to the various texts. The scores are then scaled with a linear transformation with a mean score of 500 points and a standard deviation of 100 points. The ePIRLS has five main tasks, each taking approximately 40 min to complete. The participants were randomly assigned to one or two of these five main tasks, with all tasks including both selected responses (i.e., multiple-choice formats and selection of links from a Google-like search result page) and constructed responses (i.e., short responses). See Fig. 1 for a simplified illustration. Note that this illustration of the procedure used to estimate the PIRLS and ePIRLS scores is by no means comprehensive and should be considered only a simplification of the procedure used to estimate the achievement scores. Readers are recommended to see the official documentation of how to calculate the achievement scores (Martin et al., 2017).

2.3. Independent variables

The independent variables in this study were computed from answers to the self-reported student questionnaire. We included two items where participants reported their use of digital devices for schoolwork at school and at home. The items were answered on a scale ranging from 0 (never use computers for schoolwork) to 3 (every/almost every day). We used two variables where students reported their use of academic digital reading activities: (1) finding and reading information on the internet, and (2) preparing reports and presentations. Both items were answered on a 3-point scale ranging from 0 (no time) to 2 (>30 min). Table 1 provides an overview of the variables we included in this study, as well as the variable code names in the PIRLS 2016 codebook. Table 2 shows the descriptive statistics and correlation matrices of all the variables included in this study.

2.4. Statistical analyses

Since ePIRLS contains data for students who are nested in schools within countries, the data structure can be considered hierarchical. Thus, some proportion of the variance in students' ePIRLS achievement scores might be explained by differences between schools and between countries. Therefore, an appropriate statistical analysis to apply to this dataset must account for between-group differences in the outcome variable. Therefore, a multilevel model (also known as a linear mixed-effects model) is warranted. In this type of model, the intercept and slopes are estimated as random effects (i.e., the intercept for each school and country can be estimated freely). Prior to fitting the data into a multilevel model, we ran a null model where we tested for homogeneity within clusters on digital reading comprehension scores on two levels (i.e., students and schools). We then calculated the intraclass correlation (ICC), which was 0.36, which revealed moderate homogeneity within the clusters of the dataset. Therefore, multilevel analyses with moderators (i.e., interaction terms) and normalized student weights were chosen as the statistical model to address our research questions.

Although the ePIRLS dataset also contains data at the country level, it is not recommended to apply multilevel models with three or more levels for this dataset because the number of schools participating in each participating country is not sufficient to warrant three-level modeling (Foy & O'Dwyer, 2013).

The ePIRLS dataset contains five plausible values and weights for students' digital reading achievements; therefore, we regressed all the predictors used in this study on one plausible value with the overall student weights (LaRoche et al., 2015) and then repeated this procedure for the other plausible values before ultimately aggregating the results (Rubin, 1987; von Davier et al., 2009). Data preparation and calculation of descriptive statistics were conducted in R Studio (version 4.2.2; R Core Team, 2022) using the ‘intsvy’-package (Caro & Bicek, 2017). Multilevel model analyses were conducted with the “lme4” package (Bates et al., 2017). Level 1 (student level) of the multilevel model is then modeled as follows:

$$Yij = \beta 0j + \beta 1 \ldots \beta 14ij + \varepsilon ij \quad (1)$$

where Yij represents the overall digital reading achievement score for student “i” in school “j”. $\beta 0j$ refers to the random intercept term for school “j”, where $\beta 1 \ldots \beta 14ij$ represents the fixed regression slopes for independent variables (i.e., digital device use at home, digital device use at school, finding and reading information online and preparing presentations and reports with digital devices), control variables (i.e., SES, gender, leisure reading frequency, reading self-concept, language use at home, and PIRLS International Benchmark score [i.e., low, intermediate, high, and advanced]) and interaction terms (i.e., PIRLS International Benchmark x digital device use at home, PIRLS International Benchmark x digital device use at school, PIRLS International Benchmark x finding and reading information online, and PIRLS International Benchmark x preparing presentations and reports with digital devices online) at level

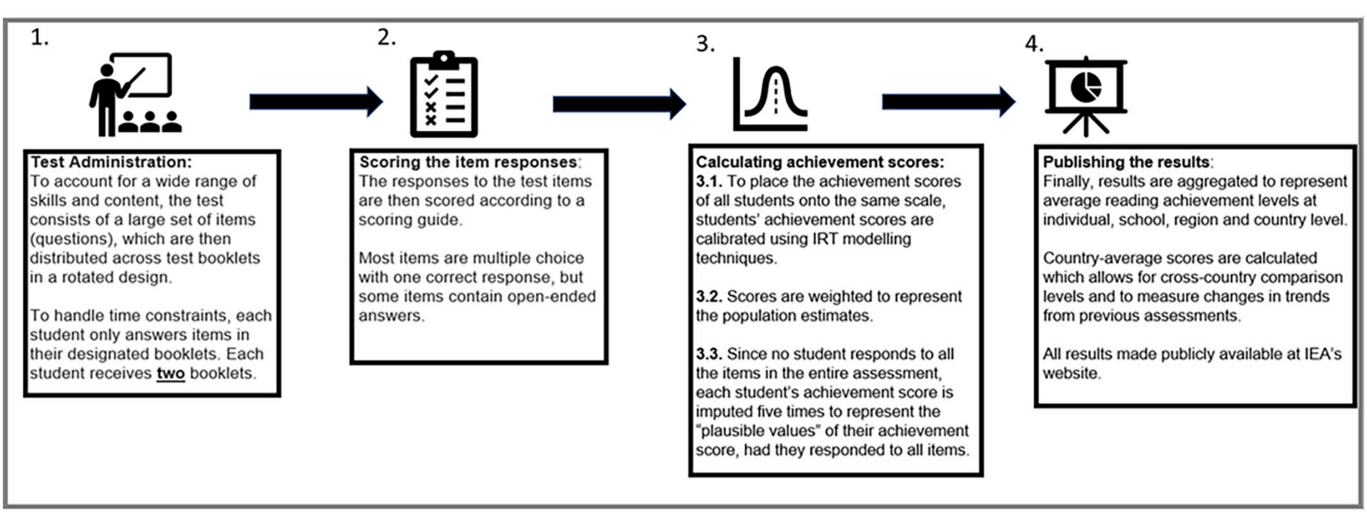

Fig. 1. A simplified illustration of the procedure for how the ePIRLS and PIRLS scores are estimated.

Table 1
Overview of the variables included in the study, including the codebook code, item wording and categories per variable.

Variables	PIRLS Codebook code	Item wording	Response categories	Scale level
Language status	ASBG03	*How often do you speak (language of testing) at home?*	0 = Never 1 = Sometimes 2 = Almost always 3 = Always	Ordinal
Gender	ITSEX	*Which gender are you?*	0 = Girl 1 = Boy	Nominal
Leisure reading frequency	ASBR05	*How often do you do read for fun outside of school?*	0 = Never or almost never 1 = Once or twice a month 2 = Once or twice a week 3 = Every day or almost every day	Ordinal
Reading self-concept	ASDGSCR	Ordinal scale for self-concept items (ASBR07A-F)	0 = Low self-concept 1 = Medium self-concept 2 = High self-concept	Ordinal
SES	ASDGHRL	Ordinal scale for home resources for learning	0 = Few resources 1 = Some resources 2 = Many resources	Ordinal
General use of digital devices for schoolwork.	ASDG09A & ASDG09B	*How often do you use a computer or tablet for schoolwork? (At home and at school)*	0 = Never or almost never 1 = Once or twice a month 2 = Once or twice a week 3 = Every day or almost every day	Ordinal
Academic digital reading activities	ASBG10A & ASBG10B	*How much time do you spend using a computer or tablet to do these activities for your schoolwork on a normal school day? (finding and reading information and preparing reports and presentations)*	0 = No time 1 = 30 min or less 2 = >30 min	Ordinal
Print reading comprehension	ASRIBM01–05	International reading scale benchmark reached	0 ≥ 400 but <475 (Low) 1 = ≥ 475 but <550 (Intermediate) 2 = ≥ 550 but <625 (High) 3 = ≥ 625 (Advanced)	Ordinal

Table 2
Descriptive statistics and Spearman correlations for all variables in the study (complete sample).

Variable	1	2	3	4	5	6	7	8	9	10	11
1. Digital device use for schoolwork at home	–										
2. Digital device use for schoolwork at school	0.24**	–									
3. Reading and finding information	0.20**	0.15**	–								
4. Preparing presentations and reports	0.16**	0.13**	0.38**	–							
5. Language use at home	−0.09**	-0.06**	−0.08**	−0.05**	–						
6. Leisure reading frequency	0.07**	0.06**	0.08**	0.09**	0.02**	–					
7. Gender	-0.01*	0.01**	-0.03**	−0.08**	−0.02**	−0.11**	–				
8. Reading self-concept	-0.04**	-0.04**	0.04**	0.07**	0.04**	0.14**	−0.07**	–			
9. SES	−0.04**	0.03**	0.03**	0.07**	0.06**	0.11**	−0.01**	0.21**	–		
10. Print reading comprehension (PIRLS)	−0.13**	−0.11**	−0.02**	0.06**	0.09**	0.05**	−0.08**	0.44**	0.34**		
11. Digital reading comprehension (ePIRLS)	−0.10**	-0.08**	0.01**	0.08**	0.05**	0.05**	−0.09**	0.46**	0.35**	0.82**	–
N	83,301	81,537	83,818	82,132	83,769	83,131	85,462	83,332	72,833	85,463	85,463
M	1.90	1.26	0.99	1.09	2.21	1.94	–	2.28	1.21	546,82	549.83
SD	1.10	1.11	0.66	0.79	0.96	1.08	–	0.76	0.47	77.86	75.05

Note. The sample size may vary slightly because of missing data.
* $p < .05$.
** $p < .01$.

1. εij represents the random error term for student "i" within school "j". The intercept should therefore be interpreted as the average digital reading comprehension score for a struggling reader (i.e., obtaining a low level on the PIRLS International benchmark) when all other predictors are held constant. The interaction terms then represent the average change in digital reading comprehension given a one-unit increase in the interaction between the print reading comprehension level and the frequency of digital device use/digital reading activities.

Level 2 (school level) of the multilevel model is then modeled as follows:

$$\beta 0j = \gamma 00 + \mu 0j \tag{2}$$

where γ00 refers to the grand mean for the two levels associated with the model intercept. $\mu 0j$ is the random error term for school "j". The final multilevel model equation, obtained by combining Eqs. (1) and (2), is then modeled as follows:

$$Yij = \gamma 00 + \beta 0j + \beta 1 \ldots \beta 14ij + \mu 0j + \varepsilon ij \tag{3}$$

The independent variables might share an inherent dependency on each other since digital reading activities cannot take place without the use of digital devices. In addition, the wording of the items for general digital device usage asks about usage over a longer time scale (i.e., monthly, weekly, and daily usage). In contrast, the items for digital reading activities ask about the frequency “on a typical school day”; these differences are difficult to compare directly. Therefore, we ran four random intercept fixed slope models for the independent variables, which means we ran one model with digital device use for schoolwork at home and one for digital device use at school, including interaction terms with print reading comprehension scores for each of these variables and two other models for academic digital reading activities with interaction terms. For each multilevel model, we used a grand mean centering on the predictor variables. Grand mean centering adjusts the interpretation of the intercept so that it represents the expected digital reading comprehension score when the grand-mean centered predictor variable is at its mean (Hoffman & Walters, 2022).

When interpreting the results shown in Table 3, please remember that the intercept represents the average digital reading comprehension score for struggling readers (i.e., students with a “low” PIRLS international benchmark, which is the ordinal variable representing the print reading comprehension level). The main effects represent associations with struggling readers' digital reading comprehension scores. The interaction effects then represent how these relationships are associated with nonstruggling readers' digital reading comprehension, meaning that a positive interaction represents an increase in the digital reading comprehension score for students who achieve higher PIRLS international benchmark scores.

3. Results

Table 2 presents the descriptive statistics for the variables included in this study, including a correlation table. The results revealed a moderate positive correlation between digital device use at home and at school ($r = 0.24$) and a moderate positive correlation between the variables reflecting meaningful academic digital reading activities: finding and reading information online and preparing presentations and reports ($r = 0.38$). Therefore, separate multilevel models for each predictor variable are warranted to avoid multicollinearity. In this study, we used variables measuring digital device use at school and at home to investigate research question 1. To investigate research question 2, we use the variables “finding and reading information online” and “preparing presentations and reports”. In addition, we used language use at home, leisure reading frequency, gender, reading self-concept, SES, and print reading comprehension as control variables to predict digital reading comprehension.

Our first research question was as follows: “Does the frequency of the general use of digital devices for schoolwork relate to digital reading comprehension differently between struggling and nonstruggling readers?”. As seen in Table 3 in Model 1, neither the association between digital device use at home nor the interaction effects with print reading comprehension were statistically significantly associated with digital reading comprehension after controlling for digital device use at school and the other control variables (i.e., language use at home, leisure reading frequency, gender, SES, reading self-concept, and print reading comprehension). Model 2 in Table 3 shows that the frequency of digital device use at school is negatively associated with struggling readers' digital reading comprehension (β = −4.60, SE = 0.89, $p < .01$). The statistically significant interaction effect indicated that the association between digital device use at schools and digital reading comprehension became positive among students with higher levels of print reading comprehension (intermediate benchmark: β = 5.65, SE = 1.34, $p < .01$; high benchmark: β = 7.47, SE = 0.78, $p < .001$; advanced benchmark: β

Table 3
Results from the multilevel models with two levels (i.e., the student level and the school level).

Variable	Model 1	Model 2	Model 3	Model 4
Intercept	404.24 (1.74)***	404.92 (1.86)***	403.49 (1.77)***	404.63 (1.73)***
Language use at home	−1.04 (0.33)*	−0.93 (0.30)**	−0.77 (0.35)*	−0.84 (0.35)*
Leisure reading frequency	−0.04 (0.32)	−0.14 (0.29)	−0.25 (0.31)	−0.26 (0.32)
Gender	−0.84 (0.88)	−0.64 (0.90)	−0.72 (0.88)	−0.46 (0.85)
SES	15.70 (0.60)***	15.07 (0.61)***	15.47 (0.62)***	15.27 (0.63)***
Reading self-concept	13.75 (0.35)***	13.72 (0.38)***	13.72 (0.35)***	13.62 (0.35)***
Print reading comprehension	66.22 (1.10)***,[1] 112.68 (1.22)***,[2] 152.60 (1.03)***,[3]	66.59 (1.10)***,[1] 113.87 (1.25)***,[2] 154.49 (1.17)***,[3]	66.83 (1.14)***,[1] 114.11 (1.21)***,[2] 154.86 (1.14)***,[3]	66.68 (1.16)***,[1] 113.75 (1.24)***,[2] 154.38 (1.19)***,[3]
Digital device use at home	0.74 (0.78)			
Digital device use at school		−4.60 (0.89)**		
Finding and reading information online			−0.15 (1.26)	
Preparing presentations and reports				1.50 (1.09)
Interaction 1	0.07 (0.97)[1] −0.07 (0.87)[2] −0.24 (1.02)[3]			
Interaction 2		5.65 (1.34)**,[1] 7.47 (0.78)***,[2] 8.53 (1.12)***,[3]		
Interaction 3			0.99 (1.38)[1] 3.09 (1.23)*,[2] 5.67 (2.24)*,[3]	
Interaction 4				0.29 (104)[1] 1.65 (1.33)[2] 4.15 (2.18)[3]
Random effects[†]				
School-level variance $\mu 0j$ (level 2)	19.86	18.84	19.05	19.88
Student-level variance ϵijk (level 1)	208.62	208.91	209.61	209.29

Model 1 = Multilevel model for digital device use at home.
Model 2 = Multilevel model for digital device use at school.
Model 3 = Multilevel model for finding and reading information online.
Model 4 = Multilevel model for preparing presentations and reports.
Interaction 1 = *Print reading comprehension* × *Digital device use at home.*
Interaction 2 = *Print reading comprehension* × *Digital device use at school.*
Interaction 3 = *Print reading comprehension* × *Finding and reading information online.*
Interaction 4 = *Print reading comprehension* × *Preparing presentations and reports.*
*** $p < .001$.
** $p < .01$.
* $p < .05$.
† Estimates are reported as standard deviations.
[1] *Print reading comprehension level: Intermediate.*
[2] *Print reading comprehension level: High.*
[3] *Print reading comprehension level: Advanced.*

= 8.53, SE = 1.12, $p < .001$) after controlling for the associations with the control variables.

Our second research question was as follows: “Does the frequency of goal-directed digital reading activities involving digital devices relate differently to digital reading comprehension between struggling and nonstruggling readers?”. As shown in Table 3 in Model 3, we found a statistically significant interaction effect, which showed a positive association between finding and reading information online and digital reading comprehension among students with higher levels of print reading comprehension (high benchmark: β = 3.09, SE = 1.23, $p < .05$; advanced benchmark: β = 5.67, SE = 2.24, $p < .05$). The results from Model 4 in Table 3 show that neither spending time on digital devices to prepare presentations and reports nor the interaction term with print reading comprehension was statistically significantly predictive of students' digital reading comprehension after controlling for the associations with the control variables.

4. Discussion

In this study, we investigated for the first time the effects of general computer use and academic digital reading activities on digital reading comprehension in a large and representative sample of 4th- and 5th-grade struggling readers. More specifically, we wanted to examine whether digital reading comprehension was related to the use of digital devices for schoolwork both at home and at school. Moreover, we also examined how the use of digital devices for finding and reading information online and creating presentations and reports was related to digital reading comprehension. After controlling for a comprehensive set of covariates, we found that digital reading comprehension was negatively associated with the amount of digital devices used for academic work in school and for finding and reading information online. Critically, these negative effects were found only in students already struggling with print reading, whereas these relationships became attenuated for students with higher levels of print reading comprehension. No statistically significant relationships were found for the use of digital devices for academic work at home or for the time spent preparing reports and presentations with digital devices.

Studies investigating the effect of the reading medium mostly rely on comparisons between reading comprehension assignments performed either in print or on screens. When Delgado et al. (2018) examined research from 2000 to 2017 that compared the reading of printed and digital texts with respect to comprehension performance, their meta-analysis revealed an advantage for printed texts (Hedge's g = −0.21, dc = −0.21). This effect is well documented in studies that typically measured students' comprehension with digital devices in a single session. Accordingly, the effects of practicing regularly with digital devices in the classroom or doing homework still need to be studied. Extensive practice with the use of digital devices in formal educational settings could potentially diminish the advantage of paper-based reading, thus having a positive relationship with the comprehension of digital texts. Our results indicate that this assumption does not hold. In this study, we used the general use of digital devices for schoolwork inside and outside school as a proxy for studying the effects of being regularly exposed to reading media. Notably, our design and data do not make it possible to identify the underlying mechanisms of our findings, but there are several plausible explanations.

First, compared with the reading of linear (printed) texts, the reading of nonlinear digital texts, such as the reading material used in this study, has been found to be particularly challenging for readers because of the heavy load they impose on their working memory (e.g., Espinas & Chandler, 2024; Hahnel et al., 2017), which seems to be even more salient among readers with poor word decoding skills (e.g., Andresen et al., 2019; Kanniainen et al., 2019). In line with assumptions in the RSF, the processing demands resulting from poor foundational reading skills (e.g., decoding, word recognition, and orthographic knowledge) often seen among struggling readers, combined with the extra working memory load imposed by nonlinear digital texts, make good reading comprehension a particular challenge for this group of readers (Feller et al., 2024). In addition, the heavy processing demands that struggling readers experience when reading digital text may reduce their capacity to monitor their lack of comprehension (Oakhill & Cain, 2012) and use appropriate comprehension strategies to build a coherent mental model. Future research is needed to test these possibilities.

Second, our results may be related to the findings of Hautala et al. (2022), who reported that struggling readers spent more time reading task-irrelevant paragraphs than their nonstruggling peers when reading digital texts. Consequently, more time spent reading on digital devices does not necessarily lead to increased digital reading comprehension and learning. In contrast, their nonstruggling peers may have developed more efficient digital reading strategies, making them able to focus on the task-relevant paragraphs in the texts they read. One explanation for this phenomenon can be found in Naumann (2015), who explored how digital reading activities, such as navigation and information-seeking engagement, are related to digital reading task performance, including how these activities are moderated by task demands. The results revealed that information seeking engagement was positively related to navigation, meaning that students who showed high information seeking behavior made more frequent visits to task-relevant website tasks that were high in task demands. This finding suggests that adaptive navigation is predictive of digital task performance because it helps the reader identify more task-relevant pages.

A third plausible explanation for the findings could be how the digital devices are used rather than the digital device itself. Although the term “cyberloafing” was originally used to describe employees' use of the internet for nonwork-related activities during work hours (Lim, 2002; Lim & Teo, 2024), the term has increasingly been used to examine students' nonacademic use of digital devices (e.g., internet browsing, social media) during schoolwork (Saritepeci, 2020). Bergdahl et al. (2018) reported a statistically significant correlation between low academic achievement and the amount of nonacademic use of digital devices in class. Conversely, high-achieving students spent more time on task-relevant digital activities, resisting their use for entertainment and nonacademic purposes. A negative relationship between nonacademic use of digital devices and low achievement has also been reported in other studies (Sanders et al., 2023). Wu et al. (2018) reported that nonacademic use of digital devices in class was more detrimental for academic achievement than nonacademic use during schoolwork at home. Accordingly, future research should examine the specific use made by struggling readers when they are assigned digital reading tasks.

A fourth and intriguing explanation could be that these findings may be attributed to the possibility that struggling readers may receive intensive remediations via digital devices. Computer-assisted instruction is becoming increasingly common in remedial reading instruction (e.g., Kim et al., 2017; Hurwitz & Vanacore, 2023). Hence, the negative relationship between struggling readers' digital device use and digital reading comprehension may reflect more extensive use of computer-assisted instruction in remedial reading instruction. In contrast, Vargas et al. (2024) recently reported that for a sample of gifted students from primary education, the frequency of time devoted to academic digital reading and comprehension was negative, suggesting that an explanation based on remedial instruction is, at best, incomplete.

Notably, all these plausible explanations may cooccur and interact with each other, which raises the necessity for future studies to investigate how readers differ with respect to the use of digital devices for their schoolwork and how this might have different implications depending on students' level of reading comprehension.

The need to account for different levels of reading competency when analyzing large-scale assessment data is evident in our results. More specifically, our findings imply that the negative association between the general use of digital devices for schoolwork and digital reading comprehension previously reported in the literature is driven mainly by struggling readers in the primary analysis of the ePIRLS 2016 dataset

(Mullis et al., 2017).

We must acknowledge that our assessment of the general use of digital devices for schoolwork at home and at school did not sufficiently gauge how struggling readers interact with digital devices. Additionally, we may have under- or overestimated the negative association between general digital device usage for schoolwork and digital reading comprehension because this measure does not distinguish between the time spent on nonacademic-related activities and the time spent on authentic reading activities involving digital devices (Salmerón et al., 2023). A recent umbrella review focusing on the effects of youths' interactions with digital devices revealed that general screen use was associated with small-to-moderate negative effects on general learning outcomes, literacy, and various health measures. Interestingly, more nuanced interactions with digital devices (e.g., watching programs with a parent or watching educational videos) are positively associated with learning and literacy outcomes (Sanders et al., 2023). These findings suggest that further studies should include more specific activities when investigating associations between digital device usage and learning outcomes.

4.1. Limitations and further research

Our study has several important limitations. First, given the large sample size and statistically significant relationships found in this study, it is important to bear in mind that the effect sizes are quite small. Hence, caution should be applied in drawing firm educational implications from our study. However, we would still argue that our findings have theoretical relevance and could be a basis for more focused studies examining these relationships in datasets specifically collected for this purpose. Second, since this study was based on nonexperimental data from international large-scale assessments, we cannot draw causal inferences, and the psychometric properties have limitations worth considering, such as issues with measurement invariance in item responses across countries (Stiff et al., 2023). Third, our dataset contained only two variables that gauged digital reading activities, making it a rather coarse-grained measure. It would be valuable for further studies to use more fine-grained measures in experimental design. Fourth, we lacked data about why the participants struggled with reading (e.g., dyslexia). Therefore, it is necessary to conduct studies with more specific groups of struggling readers and their potential challenges and affordances related to digital reading. Fifth, countries participating in ePIRLS might not reflect a representative sample at the global level. For example, no countries from Africa, South America or Oceania were included in the ePIRLS 2016 assessment (Mullis et al., 2017). Future research should therefore try to replicate our findings in other countries, school systems, grade levels, and cohorts. Finally, our statistical approach does not warrant a firm conclusion regarding where the exact threshold for the negative associations we found between digital reading comprehension and digital device use for struggling readers may lie. Given the extensive use of digital devices in today's classrooms, this should be an important issue to address in future studies.

4.2. Conclusion

As reading both in and out of school is occurring in increasingly digital contexts, good digital reading skills are essential for academic achievement and active citizenship. The presence of struggling readers in every classroom makes it urgent to increase the currently existing knowledge regarding the difficulties they face while reading digital texts. The current body of research on this topic is characterized by small sample sizes and case studies (Anmarkrud et al., 2018). To the best of our knowledge, this is the first study in which large-scale assessment data were used to examine struggling readers' digital reading comprehension. As such, our study aims to contribute to research-informed educational practices that support digital reading for all.

Funding scheme

This work was partly supported by the Research Council of Norway through its center scheme, project number: 327377 Centre for Research in Special Education and Inclusion.

CRediT authorship contribution statement

Oscar Skovdahl: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Ladislao Salmerón:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Øistein Anmarkrud:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2024.102623.

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