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Research Article

Diminishing Marginal Utility of Technological Devices toward Academic Performance in Mathematics, Reading, and Science

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ABSTRACT

The Philippines, in its pursuit of aligning its education system with global standards, has participated in the Program for International Student Assessment (PISA) which evaluates 15-year-olds' reading, scientific, and mathematical proficiency. However, the 2022 PISA report ranked Filipino learners among the lowest five in reading, science, and mathematics. This study explores how ownership of technological devices influences student performance in these domains. Using Ordinal Logistic Regression, we analyze the 2022 PISA ordinal data for 7608 Filipino students. Results show a diminishing marginal return on academic achievement as device ownership increases. While initial access to technology boosts performance, the effect weakens as students own more devices. This trend is stronger among learners without siblings and persists regardless of internal or external digital distractions. Findings emphasize the need for balanced digital engagement. Rather than restricting access or full enablement, families and policymakers should focus on strategic technology use to enhance education, aligning with Sustainable Development Goals for quality learning.

Keywords: *Philippines, PISA 2022, Technological Devices, Academic Performance, Ordinal Regression*

Introduction

Global digitalization trends have led to a significant increase in device ownership among school-aged children. In both developed and developing countries, technological devices like smartphones, tablets, and computers are now generally accessible. Research indicates a growing prevalence of these devices in educational contexts, facilitated by efforts to advance digital literacy and integrate technology into classrooms and learning centers (GEM Report UNESCO, 2023). This increasing technology integration in education has sparked attention to how digital devices improve digital literacy and student achievement in content areas such as science, math, and reading. Research consistently shows that access to technological devices can positively impact academic

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performance, especially when used appropriately as educational resources. Studies such as those by Fonseca et al. (2014) and Drain et al. (2012) highlight this trend, signifying that technology can enhance learning by supporting self-directed exploration and facilitating access to technological resources.

Digital tools have been shown to support academic performance by improving access to information, enabling interactive learning experiences, and enhancing digital skills (Pinto & Leite, 2020). Nevertheless, the effects of device use on academic achievement, especially in areas like science vary based on usage patterns and access (F. Wang et al., 2024), and external factors such as socioeconomic status (SES) (Ghimire, 2024).

Digital adoption in the Philippines, despite the heavy use of the internet, generally lags behind neighboring countries. Internet users in the Philippines tripled from 23 million in 2010 to more than 73 million in 2020 which shows the quick expansion of the Internet over the past decade (World Bank, 2020). However, the slow adoption of digital technology in the country can be traced to a number of reasons, such as the high cost of the internet, uneven quality of internet connection, and low level of competition in digital businesses. During the global pandemic, a surge in the use of digital devices was observed in the Philippines. The data demonstrates that young people, including learners, are the driving force behind the growing use of digital technology (Giray et al., 2024). Learners in Metro Manila have the highest usage of digital devices, with 96% adoption, compared to Luzon at 64%, Visayas at 43%, and Mindanao at 41% (Inquirer, 2021).

In spite of the benefits of digital learning, issues regarding the prolonged use of these digital devices are common. Attia et al., in 2017 supports the notion that excessive exposure to these devices may distract learners, reduce attention spans, and lead to lower academic performance. Overexposure can further cause device-induced dependencies that may replace positive learning behaviors which may affect subjects that require focus (Aprianti et al., 2022). The issue is intensified by digital distraction, where learners with multiple devices experience interruptions in academic routines and reduced engagement with academic tasks, as supported by a meta-analysis conducted by Kostić & Ranđelovi (2022). The socio-emotional effects of device ownership, such as increased anxiety (Rocha et al., 2023) or dependence on digital validation (Tag et al., 2022), have also raised questions about the unintended consequences of technology-heavy environments, especially for young learners who may still lack digital self-regulation skills (Twenge et al., 2018).

Additionally, the possibility of permanent access with the use of digital technology may result in an ‘always-on’ mentality, which can lead to digital stress (Reinecke et al., 2017). According to Wrede et al., (2023), digital stress is a term used to describe the negative effects of overuse or excessive reliance on digital devices and technology, including smartphones, laptops, and other electronic devices. It may be a common problem among learners who often use technology for a variety of tasks such as communication, research, and entertainment. In the Philippines, parents and educators are increasingly concerned about the significant issue of excessive smartphone usage among adolescents (Buctot et al., 2021). The COVID-19 pandemic has also contributed to digital stress, as many Filipino students have had to shift to online classes and may struggle with the lack of in-person social support (Giray et al., 2024).

Given these concerns, there is a crucial need to explore how different levels of device ownership affect learning performance. The PISA 2022 data for the Philippines offers a unique opportunity to examine these cases on a large scale, providing insights into the relationship between technology use and academic performance among Filipino learners. Furthermore, research has not fully explored how device ownership interacts with individual factors such as the number of siblings or the vulnerability of learners to distractions, whether internal (learners get distracted by using digital resources) or external (learners get distracted by other learners who are using digital resources).

The primary objective of this study is to determine the relationship between device ownership and academic achievement in science, math, and reading using the PISA 2022 dataset. Specifically, this research aims to identify the point at which increased ownership and access to devices begin to yield diminishing returns on students' academic performance. This study contributes to the literature on educational technology by empirically examining diminishing returns in digital device ownership, a relatively unexplored area with practical implications for policy and educational planning. It seeks to bridge the gap in understanding the optimal level of device ownership that enhances academic performance without introducing negative effects. Furthermore, this research may inform policymakers and educators about the potential drawbacks of over-dependence on digital devices in education. By identifying the conditions under which technology enhances or hinders learning, this study supports the development of balanced approaches to integrating digital tools into the curriculum

Methodology

Sampling Method and Data Gathered

The data utilized in this study were obtained from the Program for International Student Assessment (PISA) 2022 results facilitated through the Philippines' Department of Education. PISA is a globally recognized assessment program that measures 15-year-old students' academic competencies across reading, mathematics, and science domains while also gathering socio-demographic information.

The data was sampled via **two-stage random sampling**, a form of **probability sampling** used to ensure representation and reduce sampling bias. In the first stage, schools were randomly selected across different regions in the Philippines. In the second stage, eligible students from the selected schools were randomly chosen to participate in the PISA assessment. This method ensures that all students within the population have an equal and independent chance of being included in the sample, enhancing the generalizability of the results. This also assures there are group independence and independence of observations. The paper then analyzed a sample size of 7608 students studying in the Philippines, including both male and female respondents. The scope of the sample is limited to students within the Philippines, ensuring the research findings are reflective of the local educational landscape. This specific age group was chosen as PISA targets students nearing the end of compulsory education, providing a critical snapshot of their academic abilities and learning contexts.

The nature of the data collected and analyzed in this study are aggregately shown in Table 1,

Table 2, and Table 3; To properly utilize an ordinal regression, the total raw score for each subject was transformed into ordinal data by slicing them into quartiles to create the Total Ordinalized Score (DV). The slicing was done in quartiles to eliminate any possibility of the Hauck-Donner effect (Gnona & Stewart, 2022; T. W. Yee, 2022)

Table 1. Ordinal Dependent Variable with corresponding quartiles

Dependent Variables	**Code**	**1**	**2**	**3**	**4**
Total Ordinalized Scores in Math	DV_MATHq	Q4 (Bottom 25%)	Q3	Q2	Q1 (Top 25%)
Total Ordinalized Scores in Reading	DV_READq	Q4 (Bottom 25%)	Q3	Q2	Q1 (Top 25%)
Total Ordinalized Scores in Science	DV_SCIEq	Q4 (Bottom 25%)	Q3	Q2	Q1 (Top 25%)

Table 2 Ordinal Independent Variable with corresponding scale

Dependent Variables	**Code**	**1**	**2**	**3**	**4**
Televisions	IV1	None	1 or 2	3 – 5	More than 5
Desktop Computers	IV2	None	1 or 2	3 – 5	More than 5
Laptop Computers	IV3	None	1 or 2	3 – 5	More than 5

Dependent Variables	Code	1	2	3	4
Tablets (e.g. iPad®, BlackBerry® Playbook™)	IV4	None	1 or 2	3 – 5	More than 5
E-book readers (e.g. [Kindle™], [Kobo], [Bookeen])	IV5	None	1 or 2	3 – 5	More than 5
Cell phones with Internet access *(i.e. smartphones)*	IV6	None	1 or 2	3 – 5	More than 5

Table 3 Other Variables with questionnaires and possible answers in Likert scale

Other Variables	Code	1	2	3	4
Number of Siblings *"How many siblings (including brothers, sisters, step-brothers, and step-sisters) do you have?"*	SIB	None	One	Two	Three or more
Endogenous Distraction *"Students get distracted by using [digital resources] (e.g. smartphones, websites, apps)"*	DIST_ENDO	Every lesson	Most lessons	Some lessons	Never or almost never
Exogenous Distraction *"Students get distracted by other students who are using [digital resources] (e.g. smartphones, websites, apps)"*	DIST_EXO	Every lesson	Most lessons	Some lessons	Never or almost never

Calculations and Models

This study employed a structured statistical approach to analyze the relationship between device ownership and academic performance. First, the Jonckheere-Terpstra Test was used to detect trend relationships among ordinal variables, following established methodologies (Davidov & Peddada, 2013; Lahcene, 2015; Pirie, 2006). All statistical assumptions of the Jonckheere-Terpstra Test were considered and were satisfied. Next, this study applied an Ordinal Logistic Regression model instead of linear regression, as PISA data are ordinal rather than continuous; furthermore, ordinal regression models can better handle non-linear relationships and varying dispersion effects, which are often ignored in linear models, this can lead to more accurate and unbiased estimates (Tutz & Berger, 2017). Compared to linear regression, ordinal regression requires a link function in which this paper explored logit and probit link functions to determine which is the most appropriate for this study. After these comparative analyses, the proportional odds assumption was tested using the Brant Test (Dolgun & Saracbasi, 2014).

As this assumption was violated, this paper follows the prescription of (Rodríguez-Arelis et al., 2024) and implemented a Generalized Multiple Ordinal Logistic Regression (GOLR) to accommodate the non-proportional odds structure of the data; also, the generalized ordinal logistic regression model can incorporate different link functions by adjusting parameters, allowing it to reproduce various link functions such as logit and probit (Fernández-Navarro, 2017) making this type of regression statistically robust (Lu et al., 2022). Lastly, to determine which devices are most critical for academic performance, this study followed the methods of Behnamian et al. (2017) and employed a Random Forest algorithm to evaluate variable importance through node significance. Table 4 shows the major regression models used in this study and was calculated using R programming (Xu et al., 2016) via R studio (Gunawan et al., 2018) due to its reputation and precision in research (Tang & Ji, 2014) via R-Studio. Table 5 shows the core R packages.

Table 4. Regression Models

Model Name	DV	IV	Statistical Test
Model_101P	DV_MATHq	IV1, IV2, IV3, IV4, IV5, IV6	Ordinal Logistic Regression - probit
Model_101L	DV_MATHq	IV1, IV2, IV3, IV4, IV5, IV6	Ordinal Logistic Regression - logit
Model_102P	DV_READq	IV1, IV2, IV3, IV4, IV5, IV6	Ordinal Logistic Regression - probit
Model_102L	DV_READq	IV1, IV2, IV3, IV4, IV5, IV6	Ordinal Logistic Regression - logit
Model_103P	DV_SCIEq	IV1, IV2, IV3, IV4, IV5, IV6	Ordinal Logistic Regression - probit
Model_103L	DV_SCIEq	IV1, IV2, IV3, IV4, IV5, IV6	Ordinal Logistic Regression - logit
Model_301	DV_MATHq	IV1, IV2, IV3, IV4, IV5, IV6	Generalized Ordinal Logistic Regression
Model_302	DV_READq	IV1, IV2, IV3, IV4, IV5, IV6	Generalized Ordinal Logistic Regression
Model_303	DV_SCIEq	IV1, IV2, IV3, IV4, IV5, IV6	Generalized Ordinal Logistic Regression
Model_901	DV_MATHr	IV1, IV2, IV3, IV4, IV5, IV6	Random Forest
Model_902	DV_READr	IV1, IV2, IV3, IV4, IV5, IV6	Random Forest
Model_903	DV_SCIEr	IV1, IV2, IV3, IV4, IV5, IV6	Random Forest

Table 5 Calculation with the corresponding R-package

Core Calculation	Core R-Package
Jonckheere Terpstra Test	"PMCMRplus" (Pohlert, 2024)
[Ordinary] Ordinal Logistic Regression	"MASS" (Venables & Ripley, 2002)
Probit vs Logit Testing	"pscl" (Simon Jackman, 2017/2024)
Brant-Wald Test	"brant" (Schlegel & Steenbergen, 2020)
Generalized Ordinal Logistic Regression	"VGAM" (T. Yee et al., 2024)
Random Forest (Decision Regression)	"randomForest" (Liaw & Wiener, 2002)

Results

Descriptive Statistics

The descriptive statistics provide an overview of the distribution of academic performance scores across different quartiles and score scales. Mathematics, Reading, and Science scores exhibit a clear upward trend across quartiles, with mean and median values aligning closely, indicating a relatively symmetric distribution (Table 6 and

Table 7). Students in the top quartile (Q1) consistently achieve scores nearly double those in the bottom quartile (Q4), highlighting a significant performance gap.

Table 7 presents the frequency distribution of scores categorized into six scales, revealing that the majority of students score between 2000 and 4000, with very few achieving beyond 5000 points. Science exhibits the highest proportion of high achievers, with 8 students surpassing 6000 points, whereas Mathematics lacks any students in this range.

Regarding device ownership (Table 8), televisions are the most commonly available devices, with over 80% of students having at least one at home. In contrast, desktop computers are the least owned, with over 70% of students lacking access to one. Tablets, e-book readers, and smartphones show similar distribution patterns, with 1 to 2 devices being the most common category. Finally, the correlation matrix (Table 9) reveals notable relationships between device ownership and academic performance. Smartphones show the highest positive correlation (0.4) with all three academic domains, while e-book readers exhibit a slight negative correlation (-0.2), suggesting potential differences in utility. Other devices, such as laptops and tablets, display weaker correlations (0.2–0.3), indicating their effect may be more context-dependent.

Table 6 Frequency Distribution for Dependent Variable with Quartile Scoring

Dependent Variable	Q4 (Bottom 25%)	Q3	Q2	Q1 (Top 25%)	Mean	Median
Total Scores in Math	3,215.44	3,585.62	4,058.24	5,953.28	3,666.80	3,585.62
Total Scores in Reading	3,042.62	3,523.77	4,160.69	6,190.20	3,626.34	3,523.77
Total Scores in Science	3,151.16	3,560.61	4,148.44	6,771.98	3,690.13	3,560.61

Table 7 Frequency Distribution for Dependent Variable with Scales of Scores

Dependent Variable	1000 or more	2000 or more	3000 or more	4000 or more	5000 or more	6000 or more	TOTAL
Total Scores in Math	0	311	1496	625	64	0	2496
Total Scores in Reading	7	573	1142	630	139	5	2496
Total Scores in Science	0	402	1334	634	118	8	2496

Table 8 Frequency Distribution for Independent Variable with Scales of Quantity

Independent Variables	None	1 to 2	3 to 5	6 or more
Television(s)	295	2050	126	25
Desktop Computer(s)	1799	627	48	22
Laptop Computer(s)	986	1264	163	83
Tablet(s)	1634	765	72	25
E-book reader(s)	2081	323	47	45
Smartphone(s)	228	1066	688	514

Table 9 Correlation Matrix

	Code	1	2	3	4	5	6	7	8	9
Dependent Variables										
1. Total Scores in Math	DV_MATH	1.0								
2. Total Scores in Reading	DV_READ	0.8	1.0							
3. Total Scores in Science	DV_SCIE	0.8	0.8	1.0						
Independent Variables										
4. Television(s)	IV1	0.2	0.2	0.2	1.0					
5. Desktop Comp(s)	IV2	0.2	0.2	0.2	0.2	1.0				
6. laptop Comp(s)	IV3	0.2	0.2	0.2	0.2	0.4	1.0			
7. Tablet(s)	IV4	0.1	0.1	0.1	0.2	0.3	0.3	1.0		
8. eBook Reader(s)	IV5	-0.2	-0.2	-0.2	0.0	0.1	0.1	0.2	1.0	
9. Smartphone(s)	IV6	0.4	0.4	0.4	0.3	0.3	0.3	0.2	0.0	1.0

Jonckheere Terpstra Test Results

The Terpstra test Results favor the trend relationship of the Devices (IVs) towards the Total Ordinalized Score (DV) with respect to Mathematics, Reading, and Science. Table 10 provides the relationship between access to various technological presence and sibling presence or academic performance in Mathematics, Reading, and Science.

Significant negative relationships were observed between the presence of siblings and access to televisions, desktop computers, laptops, and tablets, as indicated by negative Z-values and statistically significant p-values ($p < 0.05$). This suggests that families with more siblings tend to have fewer of these devices.

Table 10 Jonckheere Terpstra Test Results

Comparison	Z Value	P. Value	Adj. P. Value
Siblings and…			
…Television	(2.50)	0.01	0.01**
…Desktop Computer	(5.73)	0.00	0.00***
…Laptop Computer	(2.55)	0.01	0.01**
…Tablet	(3.68)	0.00	0.00***
…eBooks	2.14	0.03	0.03*
…Smartphone	(1.89)	0.06	0.06
Math Scores and…			
…Television	7.93	0.00	0.00***
…Desktop Computer	8.79	0.00	0.00***
…Laptop Computer	8.36	0.00	0.00***
…Tablet	3.75	0.00	0.00***
…eBooks	(8.51)	0.00	0.00***
…Smartphone	18.86	0.00	0.00***
Reading Scores and			
…Television	9.70	0.00	0.00***
…Desktop Computer	8.84	0.00	0.00***
…Laptop Computer	8.56	0.00	0.00***
…Tablet	4.66	0.00	0.00***
…eBooks	(9.45)	0.00	0.00***
…Smartphone	21.79	0.00	0.00***
Science Scores and…			
…Television	8.55	0.00	0.00***
…Desktop Computer	8.75	0.00	0.00***
…Laptop Computer	8.14	0.00	0.00***
…Tablet	4.70	0.00	0.00***
…eBooks	(8.80)	0.00	0.00***
…Smartphone	19.97	0.00	0.00***

In contrast, access to eBooks was positively related to sibling presence ($p = 0.03$), while smartphones with internet access showed no significant association ($p = 0.06$). These findings indicate that while the presence of siblings limits access to conventional devices, eBooks might be more prevalent in larger households and higher socio-economic status.

A consistent pattern emerges across Mathematics, Reading, and Science when determining the relationship between device access and academic performance. Positive relationships were found between academic performance and access to televisions, desktop computers, laptops, and tablets, all of which demonstrated highly significant Z-values and p-values ($p < 0.01$). However, eBooks showed a consistent negative relationship with performance in all domains, with strong negative Z-values suggesting they may not be as effective in supporting academic outcomes. Smartphones with internet access exhibited the strongest positive relationship, especially for Reading ($Z = 21.79$, $p < 0.01$).

The findings indicate that access to devices such as televisions, computers, and smartphones is positively related to higher academic achievement, while eBooks appear to have a negative effect. For families with more siblings, reduced access to technological devices shows potential inequities in resource distribution. Furthermore, the consistent negative relationship of eBooks with academic achievement requires further research to determine whether this is due to content quality, usability, or other factors related to learning preference.

Initial Ordinal Regression Results

Based on the fitness model analysis shown on Table 11, this paper utilized the probit link function since it has better values for log-likelihood, Null log-likelihood, Residual Deviances, and Akaike Information Criterion. G2 values were taken with precaution as prescribed by Maydeu-Olivares (2006). The Brant-Wald test encountered sparsity in certain dependent and independent variable combinations. While this may introduce some instability, the overall test results still suggest the parallel regression assumption holds as all independent variables satisfy the Brant-Wald test assumptions (Gelman et al., 2008).

Table 11 [Ordinary] Ordinal Regression (Logistic vs Probit) – Results on Quasi R^2

Regression Model Code:	**101P** (Probit)	**101L** (Logit)	**102P** (Probit)	**102L** (Logit)	**103P** (Probit)	**103L** (Logit)
Fitness of Model						
LLH (log-likelihood)	(3,110)	(3,112)	(3,068)	(3,068)	(3,113)	(3,114)
LLH Null (intercept-only)	(3,460)	(3,460)	(3,460)	(3,460)	(3,460)	(3,460)
G2	699.52	695.44	784.57	783.87	695.15	692.27
Residual Deviance	6220.86	6224.942	6135.813	6136.509	6225.236	6228.113
Akaike Information Criterion	6262.86	6266.942	6177.813	6178.509	6267.236	6270.113
Pseudo R-Squared						
McFadden	0.1011	0.1005	0.1134	0.1133	0.1004	0.1000
Maximum likelihood	0.2444	0.2432	0.2697	0.2695	0.2431	0.2422
Cragg-Uhler (Nagelkerke)	0.2607	0.2594	0.2877	0.2875	0.2593	0.2584
Brant-Wald Test p-values result						
Omnibus	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.00 ***
TV Linear (L.)	0.58	0.80	0.29	0.58	0.80	0.29
TV Quadratic (Q.)	0.93	0.35	0.31	0.93	0.35	0.31
TV Cubic (C.)	0.74	0.29	0.27	0.74	0.29	0.27
Desktop Comp. L.	0.05 *	0.08	0.50	0.05 *	0.08	0.50
Desktop Comp. Q.	0.92	0.65	0.95	0.92	0.65	0.95
Desktop Comp. C.	0.55	0.67	0.86	0.55	0.67	0.86
Laptop Comp. L.	0.81	0.75	0.17	0.81	0.75	0.17
Laptop Comp. Q.	0.06	0.02 *	0.04	0.06	0.02 *	0.04
Laptop Comp. C.	0.00 ***	0.16	0.06	0.00	0.16	0.06
Tablets C.	0.72	0.72	0.35	0.72	0.72	0.35
Tablets Q.	0.31	0.24	0.41	0.31	0.24	0.41
Tablets C.	0.27	0.76	0.32	0.27	0.76	0.32
E-book readers L.	0.76	0.19	0.12	0.76	0.19	0.12
E-book readers Q.	0.09	0.23	0.83	0.09	0.23	0.83
E-book readers C.	0.09	0.18	0.17	0.09	0.18	0.17
Smartphone L.	0.76	0.05 *	0.53	0.76	0.05 *	0.53
Smartphone Q.	0.21	0.25	0.16	0.21	0.25	0.16
Smartphone C.	0.48	0.84	0.37	0.48	0.84	0.37

Generalized Ordinal Logistic Regression Results

The Brant Test results show omnibus were significant, indicating that the proportional odds assumption holds in the ordinal regression.; therefore, this study employed Generalized Ordinal Logistic Regression (GOLR) as suggested in the paper of Rodríguez-Arelis et al.

(2024). The results from the GOLR models (Models 301P, 302P, and 303L) reveal consistent quadratic (Q.) and cubic (C.) behavior across most predictors as shown in Table 12. This indicates that the relationships between the independent variables and the dependent ordinal outcomes are non-linear, with effects increasing to a peak before tapering off or reversing.

Table 12. Generalized Ordinal Logistic Regression Models Aggregate Results

Regression Model Code: \ Variables	301P Est.	Std. Error	P. value	302P Est.	Std. Error	P. value	303L Est.	Std. Error	P. value
Intercept: 1									
Quartile 4 | Quartile 3	0.21	0.12	0.09	0.18	0.12	0.12	0.31	0.22	0.16
Intercept:2									
Quartile 3 | Quartile 2	1.01	0.13	0.00 ***	1.00	0.12	0.00 ***	1.64	0.22	0.00 ***
Intercept:3									
Quartile 2 | Quartile 1	1.81	0.13	0.00 ***	1.81	0.12	0.00 ***	2.98	0.22	0.00 ***
TV Linear (L.)	0.18	0.18	0.32	0.18	0.18	0.31	0.39	0.31	0.20
TV Quadratic (Q.)	0.75	0.14	0.00 ***	0.71	0.14	0.00 ***	1.20	0.24	0.00 ***
TV Cubic (C.)	0.30	0.09	0.00 ***	0.21	0.09	0.02 *	0.53	0.16	0.00 ***
Desktop Comp. L.	0.29	0.21	0.17	0.19	0.20	0.35	0.87	0.38	0.02
Desktop Comp. Q.	0.42	0.18	0.02 *	0.33	0.17	0.05 *	1.09	0.32	0.00 ***
Desktop Comp. C.	0.07	0.14	0.62	(0.03)	0.13	0.83	0.31	0.23	0.18
Laptop Comp. L.	0.11	0.10	0.26	0.11	0.10	0.26	0.00	0.17	0.99
Laptop Comp. Q.	0.39	0.09	0.00 ***	0.34	0.09	0.00 ***	0.48	0.14	0.00 ***
Laptop Comp. C.	0.28	0.07	0.00 ***	0.24	0.07	0.00 ***	0.35	0.12	0.00 ***
Tablets C.	0.89	0.20	0.00 ***	0.62	0.19	0.00 ***	1.18	0.33	0.00 ***
Tablets Q.	0.38	0.15	0.01 **	0.28	0.15	0.06	0.55	0.25	0.03 *
Tablets C.	(0.04)	0.11	0.70	(0.02)	0.11	0.83	(0.13)	0.19	0.47
E-book readers L.	0.36	0.13	0.01	0.49	0.13	0.00 ***	0.63	0.22	0.00 ***
E-book readers Q.	(0.42)	0.13	0.00 ***	(0.44)	0.13	0.00 ***	(0.86)	0.22	0.00 ***
E-book readers C.	(0.12)	0.13	0.35	(0.13)	0.13	0.31	(0.32)	0.22	0.15
Smartphone L.	(0.92)	0.07	0.00 ***	(1.07)	0.07	0.00 ***	(1.53)	0.11	0.00 ***
Smartphone Q.	0.20	0.05	0.00 ***	0.25	0.05	0.00 ***	0.23	0.09	0.01 **
Smartphone C.	0.24	0.04	0.00 ***	0.23	0.04	0.00 ***	0.37	0.07	0.00 ***

For predictors such as TV usage, desktop computers, and tablets, the quadratic terms were highly significant ($P < 0.05$), while the linear terms (L.) were often non-significant, demonstrating that linear approximations alone do not adequately capture these relationships. The cubic terms (C.) were occasionally significant, suggesting that only some variables, such as laptops and smartphones, exhibit more complex interactions. The intercepts, representing thresholds between outcome categories, were significant across all models, supporting the ordinal distinctions in the dependent variables. Hauck-Donner effects were not detected, indicating stable parameter estimates. While both probit (301P, 302P) and logit (303L) link functions yielded consistent findings, the logit link was slightly more sensitive to cubic behavior. These results suggest that a quadratic model, supplemented with selective cubic terms, provides the best balance between parsimony and explanatory power for these ordinal data.

Random Forest Result

The Random Forest regression results demonstrate comparable explanatory power to the findings from the Generalized Ordinal Logistic Regression models, with moderate levels of variance explained (%Var explained, R2R^2R2). Across models 901, 902, and 903, the R2R^2R2 values range from 26.52% to 30.03%, indicating that while the Random Forest algorithm captures a significant portion of the variability in the dependent variable, there is substantial unexplained variance, likely attributable to factors not included in the models or inherent data complexity.

Table 13 Random Forest Statistical Goodness of Fit

Regression Model Code	Number of Trees	No. split	% Var explained (R^2)
901	10000	263673	27.17
902	10000	441167	30.03
903	10000	378329	26.52

Discussion

Insights from Generalized Ordinal Logistic Regression

The findings consistently demonstrate the Law of Diminishing Marginal Returns of Utility, revealing that initial device ownership improves academic performance, but excessive use leads to negative effects. Different devices exhibit varying degrees of impact.

Table 14 Summary of Findings

Device	Key Findings	Real-World Applications
TV	More TVs at home are significantly lower academic performance	Schools and parents should minimize passive screen time and promote interactive educational content.
Desktop Comp-uters	Initial ownership benefits students, but overuse has drawbacks.	Schools should provide **structured computer-based learning programs** to maximize educational value
Laptop Comp-uters	Performance declines significantly with increased usage.	Schools should **limit non-educational laptop use** and train students in **effective digital study habits**.
Tablets	Early declines in academic scores, slight improvement at extreme usage.	**Blended learning** approaches should be used to integrate tablets for educational purposes, ensuring controlled use.
E-book Readers	Initially, unhelpful, but moderate use improves academic outcomes.	E-book readers should be **integrated into literacy programs** to encourage focused reading habits.
Smart-phones (with Internet access)	Helpful at low levels, but excessive use harms academic performance.	Schools and parents should enforce **screen time regulations** and **promote academic app usage** over entertainment.

In comparative analysis, TVs and laptops support the idea of diminishing returns in academic performance. A negative impact was observed for TVs with initial ownership, but academic performance declined significantly as the number of TVs increased. This may be because excessive screen time reduces study hours or replaces educational activities with entertainment. Similarly, laptops did not have a strong effect at first, but as ownership increased, academic performance dropped. This suggests that students might not be using laptops primarily for learning but for non-academic purposes like gaming or social media. Tablets and desktop computers showed more complex patterns. Tablets initially had a strong negative effect, meaning more tablets generally correlated with lower academic scores; however, a minor improvement appeared when the number of tablets was very high. Desktop computers also showed an initial decline in academic performance, but this decline eventually stabilized, likely because desktops are used for both schoolwork and entertainment but remain in shared spaces where usage may be monitored.

These findings suggest that while digital devices can be beneficial, excessive ownership may lead to distractions, reducing their positive impact on learning. To maximize their benefits, schools, and parents should encourage structured screen time, promote educational software over entertainment apps, and ensure that digital devices are used in a controlled learning environment rather than for passive consumption.

Table 15 Decision Regression Results (via Random Forest)

Regression Model Code:	% Inc MSE 3010	3020	3030	Inc Node Purity 3010	3020	3030
Dependent Variable						
Total Scores in…	MATH	READ	SCIE	MATH	READ	SCIE
Independent Variable						
Television(s)	24,296	11,229	13,157	57,438,082	28,552,606	34,911,083
Desktop Computer(s)	36,200	21,399	28,097	58,514,873	32,508,647	50,555,965
Laptop Computer(s)	27,621	17,696	24,117	61,689,590	35,849,471	54,441,995
Tablet(s)	15,299	9,663	10,447	43,924,206	25,132,142	34,153,183
Smartphone(s)	38,949	20,942	31,117	69,261,758	35,338,884	50,043,349
eBook Reader(s)	210,959	112,823	147,623	279,625,664	144,137,596	198,689,619

Insights from Random Forest

The results from the Decision Regression analysis using Random Forest provide robust statistical insights into the relationship between different devices owned and their impact on total academic scores in Mathematics, Reading, and Science. The % Inc MSE (Mean Squared Error) metric indicates the relative importance of each device in predicting the dependent variable, with higher values denoting greater predictive significance. Among the devices, eBook Readers emerge as the most significant predictor across all academic domains, showcasing the highest % Inc MSE scores: 211,024 for Mathematics, 112,562 for Reading, and 146,823 for Science. These findings align with the Inc Node Purity metric, which measures the reduction in residual impurity attributable to splits involving the device. Here, eBook Readers again dominate, achieving Inc Node Purity values of 281,787,124 for Mathematics, 143,305,879 for Reading, and 197,893,410 for Science. The Generalized Ordinal Logistic Regression analysis corroborates these findings, indicating a U-shaped relationship for eBook Readers, highlighting their unique non-linear impact on academic performance, while most other devices exhibit a downward trend. These statistical results underscore each device's nuanced role in shaping educational outcomes. Interestingly, other devices such as Smartphones and Desktop Computers also show moderate importance, particularly in Mathematics, with notable Inc Node

Purity values of 69,503,861 and 57,854,126, respectively. In contrast, Tablets consistently rank lower in both metrics while Televisions are the lowest, suggesting these devices have a less pronounced role in influencing positive academic performance.

Insight from Box Plots

Throughout all box plot analyses, a diminishing marginal return of utility is evident to almost all devices, with the exception of smartphones.

Television(s)

Figure 1 shows a strong diminishing return for television; external distractions on learners are less pronounced in terms of decreased performance. This strong negative effect of TV is congruent with the literature that shows heavy TV viewers tend to have poorer academic achievement and mathematical reasoning (Shejwal & Purayidathil, 2006) Additionally, watching more than two hours of television per day at a young age can lead to lower performance in reading and numeracy (Mundy et al., 2020). Although educational TV shows have a positive effect on a child (Supper et al., 2022), this downward trend suggests TV shows in the Philippines are not positive towards the scholastic well-being of students.

Desktop Computer(s)

The box plot in Figure 2 shows the interaction between the number of desktop computers at home, student performance, and levels of internal and external distractions during lessons. These findings support old (Fairlie et al., 2010) studies and current (Djinovic & Giannakopoulos, 2024) studies that home computers provide ease of completing school assignments and reducing nonproductive activities. Second, box plot analysis also shows that learners with 1 or 2 desktop computers consistently achieve higher scores than those without computers or those with more than five desktop computers. This result is similar to the field study of Fairlie & Robinson (2013) where they found no significant effects on grades, test scores, or other educational metrics despite increased computer ownership. Lastly, higher distraction levels (every lesson) correspond to lower scores across all ownership categories while minimal distractions yield (never or almost never) yield the highest scores, especially for learners with 1 or 2 computers, suggesting unrestricted computer use can negatively affect grades (Kutzhan et al., 2023).

Laptop Computer(s)

Accounting distraction, box plot analysis (Figure 3) shows learners with 1 or 2 laptops at home generally achieve higher scores while learners with no laptops generally perform the worst; this is similar to the findings of Reisdorf et al., (2020) that laptop ownership can be beneficial, particularly for students who do not have one, which has implications for university policies on providing access to laptops. A diminishing return becomes present when the number of laptops owned per person increases, suggesting the ideal number of owned laptops is 1 or 2. For instance, learners with more than five laptops tend to perform worse, possibly due to overexposure leading to inefficiency or distraction. Lower distraction levels (never or almost never) are linked with better scores, especially for students with one or two laptops. High endogenous distraction levels (every lesson) negatively affect performance across all laptop ownership categories. This can be explained by the studies of Ravizza et al., (2017) where nonacademic internet use on laptops during class is common and inversely related to class performance, even after accounting for motivation, interest, and intelligence.

Tablet(s)

Initially, academic performance tends to increase with 1 to 2 tablets. However, as the number of tablets increases (3–5 or more than 5), this benefit plateaus or even declines across most distraction levels. Higher distraction levels correspond to reduced academic performance, even with an optimal number of tablets. Learners with fewer distractions maintain relatively consistent performance regardless of tablet ownership, though the diminishing returns trend remains visible. The dampening effect of distraction may be attributed to the high motivation and engagement of students in the learning process and watching educational videos as the touch screen size is bigger as compared to smartphones (Rahali et al., 2023). Learners with no tablets often perform similarly to those with excessive devices, indicating that owning more tablets does not guarantee higher scores.

e-book reader

E-book readers, although positive, have the weakest additional positive effect on learners and have the lowest maxima in the curvature of diminishing marginal return among all devices; more so, learners with no e-book readers often perform at least the same as those with e-book readers. This implies that while e-books may increase engagement, they do not necessarily translate to better academic performance on their own. This is analogous to the findings of Sattar Chaudhry (2014), where his experiment with fourth-grade students shows that students enjoyed reading e-books more than paperback, but the difference in comprehension levels was not significant. Nonetheless, interactive e-books, which include multimedia and annotation features, have been shown to improve learning outcomes and engagement in various subjects (Lai et al., 2017); thus, the authors of this paper deduced that the weak effect of e-book readers among Filipino students is due to the lack of an "artificially intelligent e-textbook" such as those of e-books of McGraw-Hill's Smartbook (Badir et al., 2023) and Cengage's MindTap (Mafunda & Swart, 2020) where the learners can prompt queries to the e-book itself to understand further complex topics.

Smartphones

Among all devices, the ownership of smartphone device(s) has the most favorable results as it has the biggest compounding positive effect on academic performance and the highest maxima should it exhibit the law of marginal return of utility. This finding is similar to the study of J. C. Wang et al., (2023) where frequent smartphone use among elementary students can lead to better academic performance due to increased access to learning resources and educational apps that enhance learning effectiveness. Nonetheless, smartphones can be a source of distraction, diverting students' attention away from academic tasks. This is particularly evident in older students, where in-class smartphone use negatively correlates with grades (Abd. Rashid et al., 2020; Bjerre-Nielsen et al., 2020).

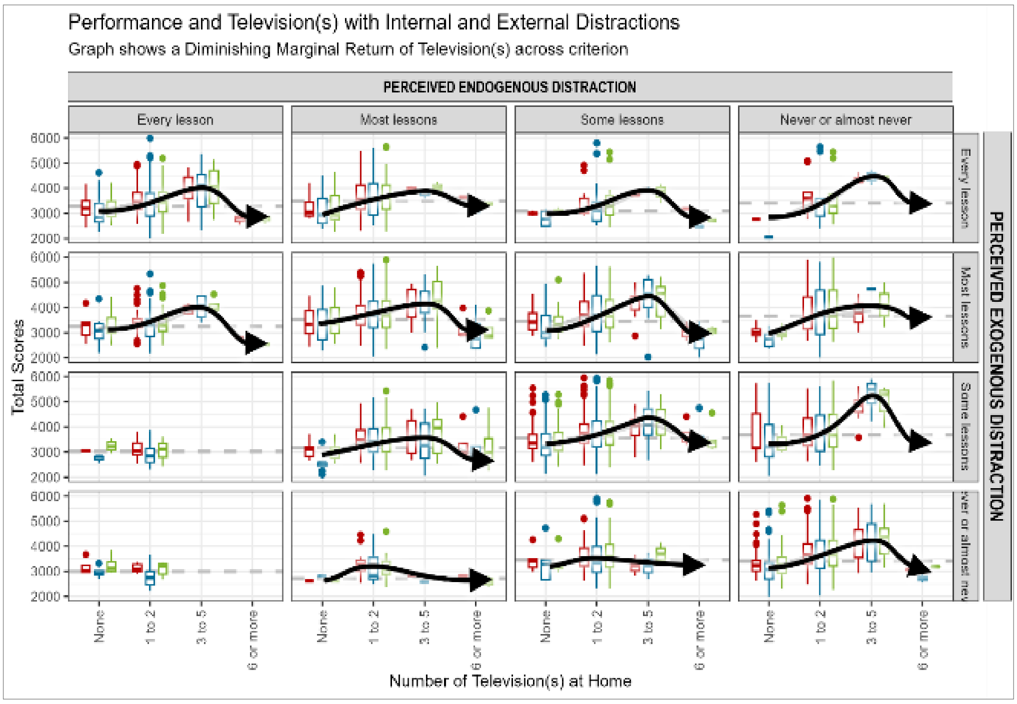

Figure 1. Boxplot for Television(s) (Red = Score Math, Blue = Score in Reading, Green – Score in Science)

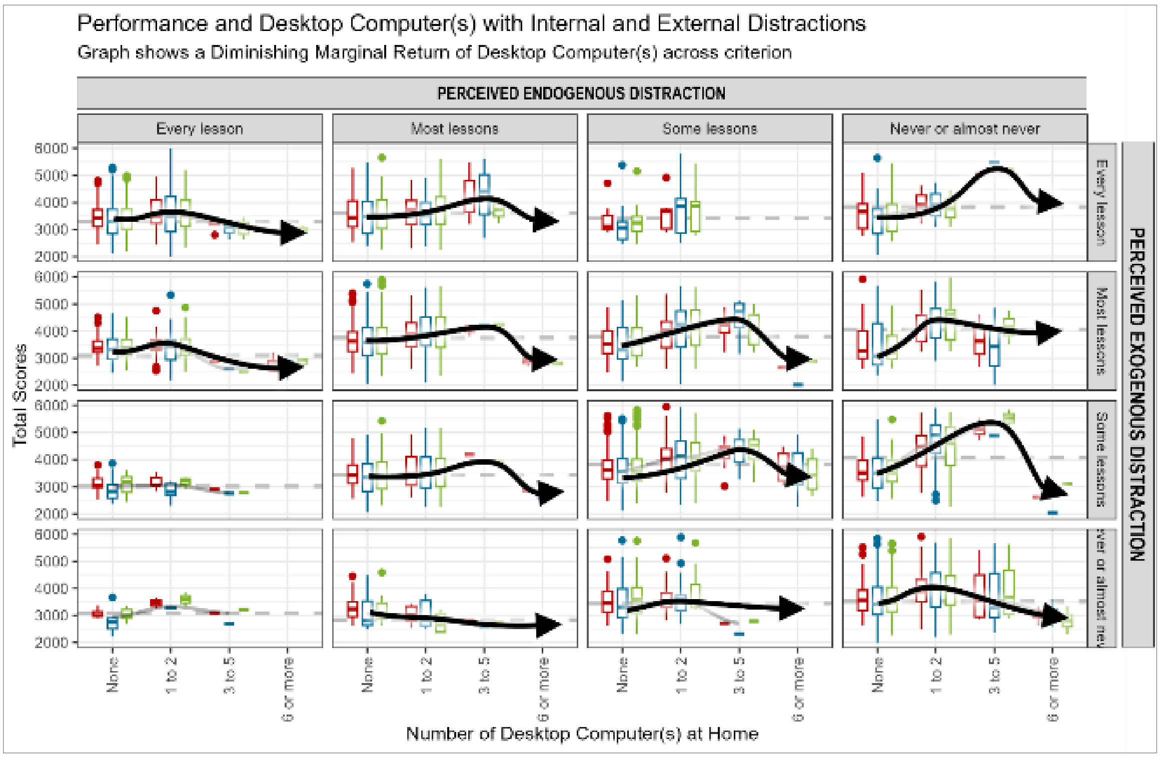

Figure 2 Boxplot for Desktop Computer(s) (Red = Score Math, Blue = Score in Reading, Green – Score in Science)

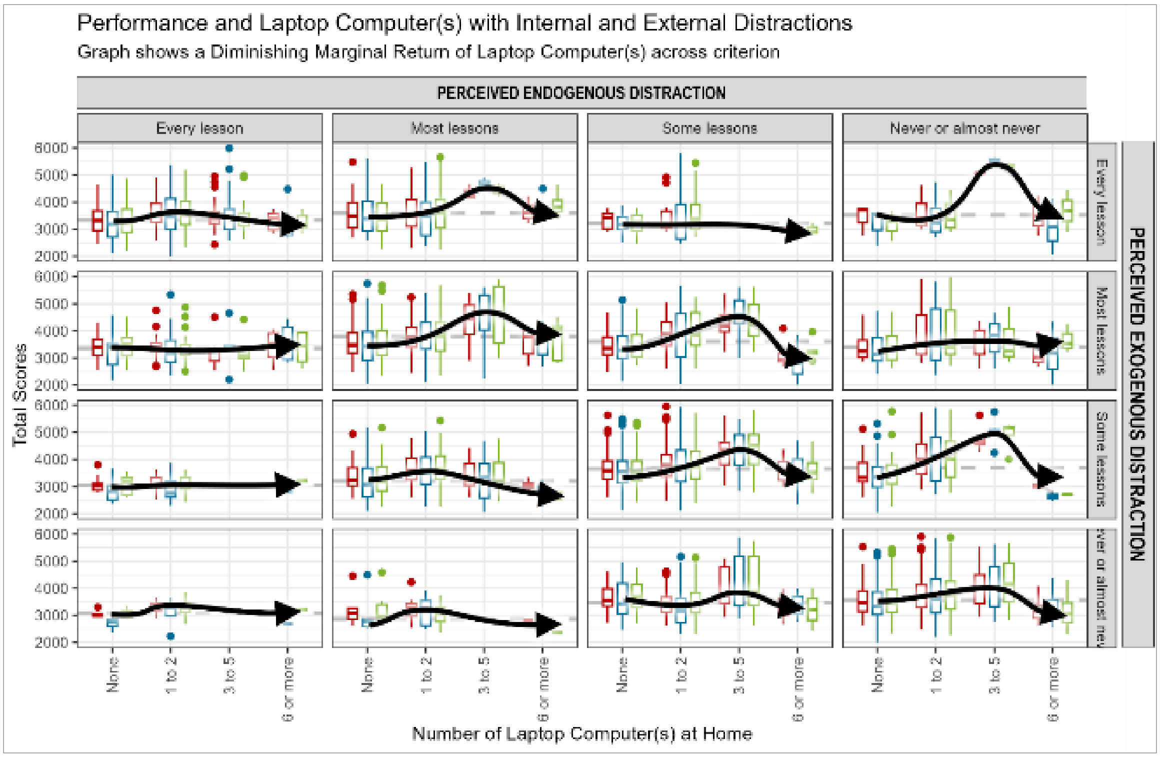

Figure 3 Boxplot for Laptop Computer(s) (Red = Score Math, Blue = Score in Reading, Green – Score in Science)

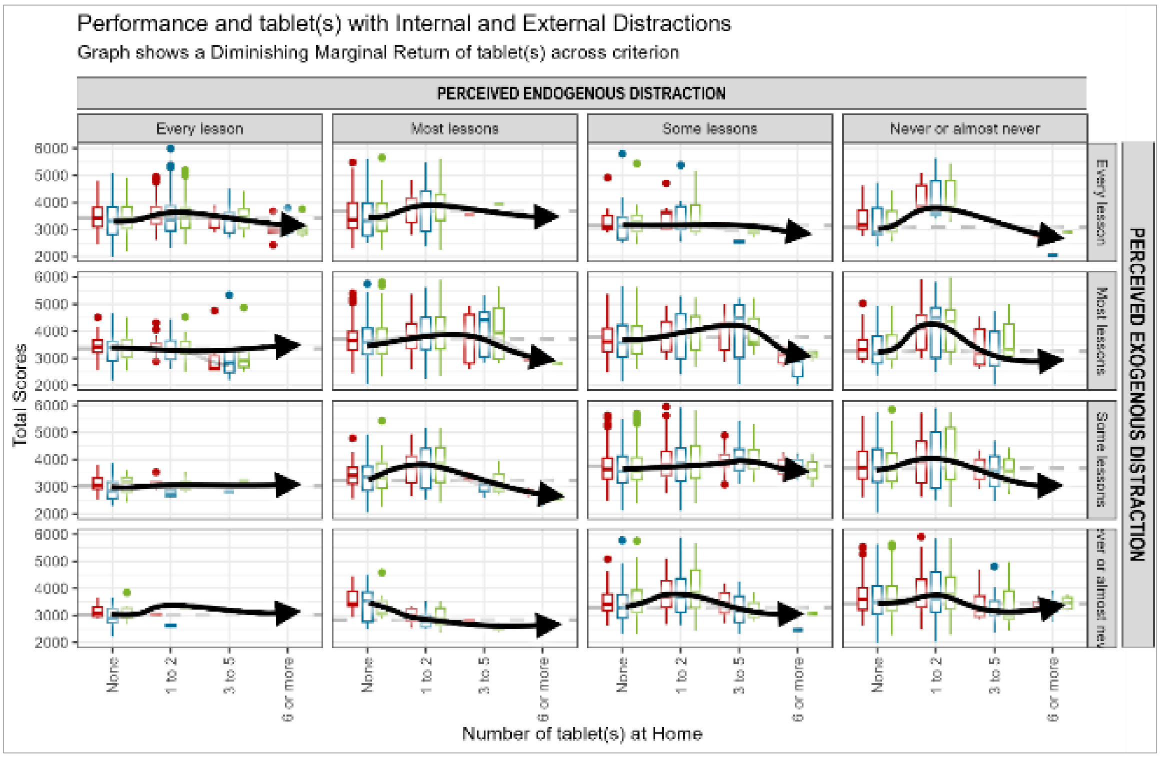

Figure 4. Boxplot for Tablet (Red = Score Math, Blue = Score in Reading, Green – Score in Science)

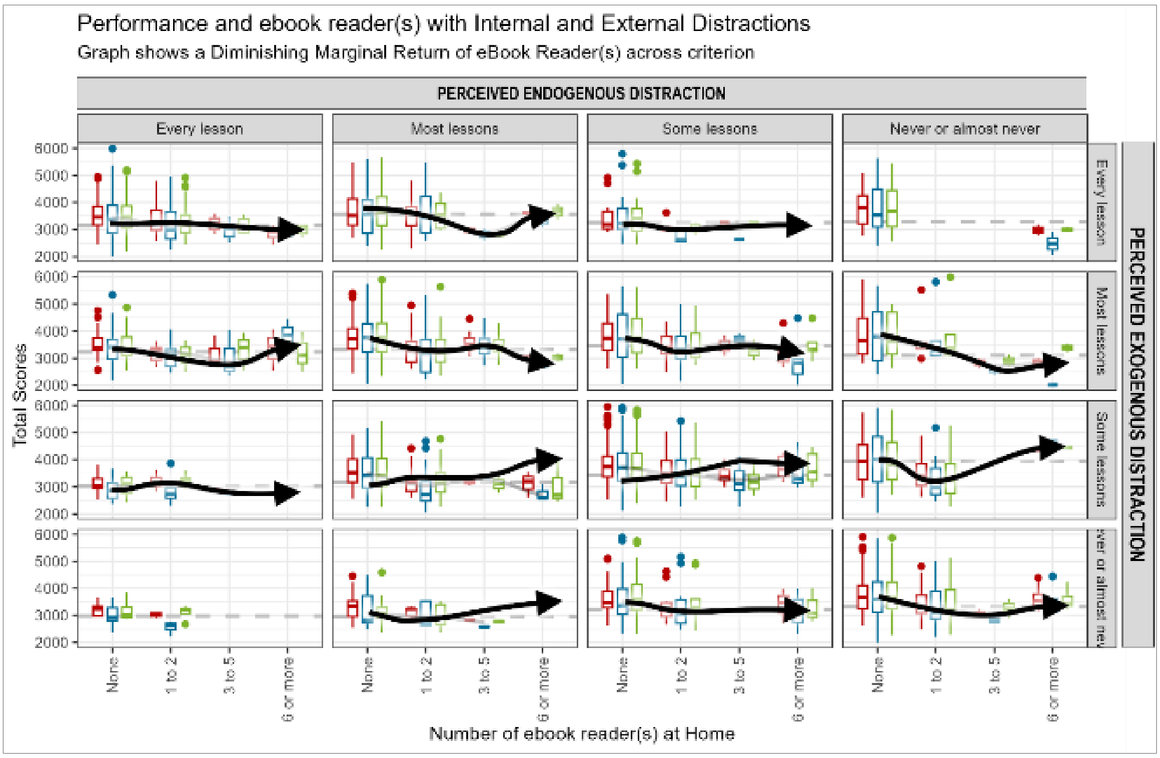

Figure 5. Boxplot for eBook Reader (Red = Score Math, Blue = Score in Reading, Green – Score in Science)

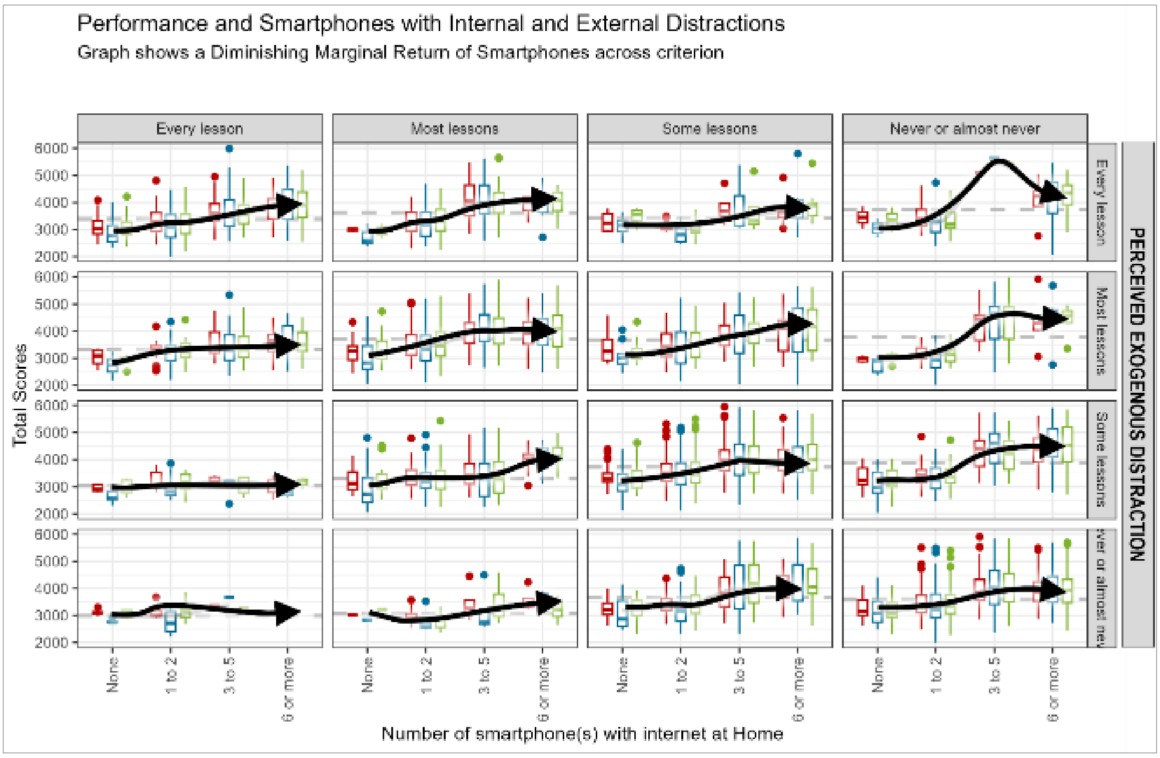

Figure 6. Boxplot for Smartphones (Red = Score Math, Blue = Score in Reading, Green – Score in Science)

Conclusion

Explored Theories

This study highlights the **Law of Marginal Return of Utility** in the context of digital devices and academic performance, demonstrating that while access to technology can enhance learning, excessive or improper use may lead to diminishing returns. The effects of digital devices vary across subjects, with math and science being more sensitive to device availability and type, whereas reading exhibits more subtle trends.

Applying **Distraction-Conflict Theory**, this research distinguishes between endogenous distractions (self-induced, e.g., using smartphones for non-academic purposes) and exogenous distractions (external, e.g., being distracted by others using devices). The findings suggest that exogenous distractions negatively impact academic performance more than endogenous ones.

For the interplay of devices and academic performance, this paper has supported the theory of **Media Multitasking & Task Switching** (Zhou & Deng, 2023) and **Technological Affordances** in Learning theories that suggest having multiple devices can enhance learning by allowing students to efficiently switch between tasks (Alzahabi et al., 2017), access diverse educational resources, and integrate different forms of digital learning. This study also expanded these theories by demonstrating that owning too many devices leads to diminishing returns, ultimately harming academic performance. The findings suggest that excessive device ownership may introduce distractions, reduce focus, and create inefficiencies in digital learning, reinforcing the importance of strategic and purposeful technology use in education.

Recommendation

Parents may gift their child a smartphone that is partnered with monitoring and guidance to deliver the student to a scholastic upbringing. Granted this was accomplished (as it is common for Filipino learners to have their own respective smartphones with internet access), the parents should then prioritize acquiring desktop or laptop computers for their children over tablets, e-books, and especially televisions (see

Figure 7). The government, the Philippines Department of Education (DepEd), should continue supporting DepEd's public educational mobile app available in the Google Appstore since most learners can access mobile devices. Also, DepEd should also steer educational innovation where the use of smartphones is strategically integrated into curriculums to maximize students' competencies. Lastly, this paper recommends researchers expand this study by exploring how device peripherals (such as wireless mice, earphones, external drives, etc.) specifications (such as the size of RAM (Random Access Memory), CPU brands, the size of the monitor, laptop weight, etc.) and the manner of usage (e.g. frequency or duration of usage, ergonomics, etc.) affect academic performance.

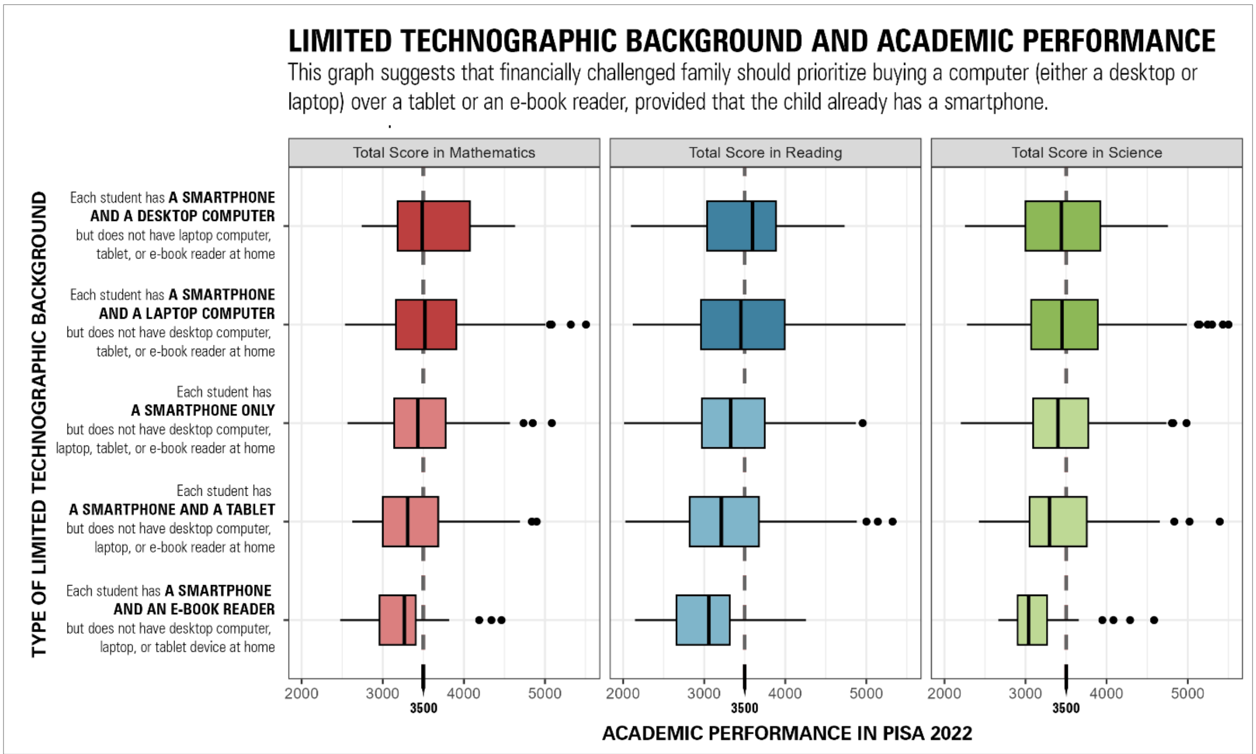

Figure 7 Academic Performance among learners with very limited devices owned

Others

Author contributions

Gerald S. Martos initiated the study on PISA, gathered the dataset, and provided the theoretical foundation for the education-related aspects of the research. He played a key role in interpreting the study's applied significance and contextualizing its implications for the Philippine education system through his expertise and experience in the field.

David S. Jose did all statistical computations and data science through R programming, ensuring the accuracy and rigor of the analysis. He conducted the statistical interpretation, all data visualizations, and all data explorations and provided the theoretical framework related to the law of diminishing marginal returns, enhancing the study's depth in economic and statistical perspectives.

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References

Abd. Rashid, J., Abdul Aziz, A., Abdul Rahman, A., Saaid, S. A., & Ahmad, Z. (2020). The influence of mobile phone addiction on academic performance among teenagers. *Jurnal Komunikasi: Malaysian Journal of Communication*, *36*(3), 408–424. https://doi.org/10.17576/JKMJC-2020-3603-25

Alzahabi, R., Becker, M. W., & Hambrick, D. Z. (2017). Investigating the relationship between media multitasking and processes involved in task-switching. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(11), 1872–1894. https://doi.org/10.1037/xhp0000412

Aprianti, F., Dayurni, P., Fajari, L. E. W., Pernanda, D., & Meilisa, R. (2022). *The impact of gadgets on student learning outcomes: A case study in indonesia junior high school students*. https://doi.org/10.5281/ZENODO.7446724

Attia, N., Baig, L., Marzouk, Y. I., & Khan, A. (2017). The potential effect of technology and distractions on undergraduate students' concentration. *Pakistan Journal of Medical Sciences*, *33*(4). https://doi.org/10.12669/pjms.334.12560

Badir, A., Tsegaye, S., & Girimurugan, S. (2023). The effect of mcgraw-hill connect online assessment on students' academic performance in a mechanics of materials course*. *International Journal of Engineering Education*, *39*(5), 1242–1255. Scopus.

Behnamian, A., Millard, K., Banks, S. N., White, L., Richardson, M., & Pasher, J. (2017). A systematic approach for variable selection with random forests: Achieving stable variable importance values. *IEEE Geoscience and Remote Sensing Letters*, *14*(11), 1988–1992. IEEE Geoscience and Remote Sensing Letters. https://doi.org/10.1109/LGRS.2017.2745049

Bjerre-Nielsen, A., Andersen, A., Minor, K., & Lassen, D. D. (2020). The negative effect of smartphone use on academic performance may be overestimated: Evidence from a 2-year panel study. *Psychological Science*, *31*(11), 1351–1362. https://doi.org/10.1177/0956797620956613

Buctot, D. B., Kim, N., & Kim, S.-H. (2021). Personal profiles, family environment, patterns of smartphone use, nomophobia, and smartphone addiction across low, average, and high perceived academic performance levels among high school students in the philippines. *International Journal of Environmental Research and Public Health*, *18*(10). https://doi.org/10.3390/ijerph18105219

Davidov, O., & Peddada, S. (2013). Testing for the multivariate stochastic order among ordered experimental groups with application to dose–response studies. *Biometrics*, *69*(4), 10.1111/biom.12070. https://doi.org/10.1111/biom.12070

Djinovic, V., & Giannakopoulos, N. (2024). Home computer ownership and educational outcomes of adolescents in greece. *Education Economics*, *32*(4), 523–537. https://doi.org/10.1080/09645292.2023.2243550

Dolgun, A., & Saracbasi, O. (2014). Assessing proportionality assumption in the adjacent category logistic regression model. *Statistics and Its Interface*, *7*(2), 275–295. https://doi.org/10.4310/SII.2014.v7.n2.a12

Drain, T., Grier, L., & Wenying, S. (2012). Is the growing use of electronic devices beneficial to academic performance? Results from archival data and a survey. *Issues In Information Systems*, *13*(1), 225–231. https://doi.org/10.48009/1_iis_2012_225-231

Fairlie, R. W., Beltran, D. O., & Das, K. K. (2010). Home computers and educational outcomes: Evidence from the nlsy97 and cps. *Economic Inquiry*, *48*(3), 771–792. https://doi.org/10.1111/j.1465-7295.2009.00218.x

Fairlie, R. W., & Robinson, J. (2013). Experimental evidence on the effects of home computers on academic achievement among schoolchildren. *American Economic Journal: Applied Economics*, *5*(3), 211–240. https://doi.org/10.1257/app.5.3.211

Fernández-Navarro, F. (2017). A generalized logistic link function for cumulative link models in ordinal regression. *Neural Processing Letters*, *46*(1), 251–269. https://doi.org/10.1007/s11063-017-9589-3

Fonseca, D., Martí, N., Redondo, E., Navarro, I., & Sánchez, A. (2014). Relationship between student profile, tool use, participation, and academic performance with the use of Augmented Reality technology for visualized architecture models. *Computers in Human Behavior*, *31*, 434–445. https://doi.org/10.1016/j.chb.2013.03.006

Gelman, A., Jakulin, A., Pittau, M. G., & Su, Y.-S. (2008). A weakly informative default prior distribution for logistic and other regression models. *The Annals of Applied Statistics*, *2*(4). https://doi.org/10.1214/08-AOAS191

GEM Report UNESCO. (2023). *Global education monitoring report 2023: Technology in education: a tool on whose terms?* (1st ed.). GEM Report UNESCO. https://doi.org/10.54676/UZQV8501

Ghimire, N. (2024). *Understanding Disparities: Examining Demographic, socioeconomic, and Linguistic Impacts on U.S. Students' Outcomes in Reading, Math, and Science*. https://doi.org/10.31124/advance.24226158.v1

Giray, L., Nemeño, J., Braganaza, J., Lucero, S. M., & Bacarra, R. (2024). A survey on digital device engagement, digital stress, and coping strategies among college students in the Philippines. *International Journal of Adolescence and Youth*, *29*(1), 2371413. https://doi.org/10.1080/02673843.2024.2371413

Gnona, K. M., & Stewart, W. C. L. (2022). Revisiting the wald test in small case-control studies with a skewed covariate. *American Journal of Epidemiology*, *191*(8), 1508–1518. https://doi.org/10.1093/aje/kwac058

Gunawan, A., Fong Cheong, M. L., & Poh, J. (2018). An essential applied statistical analysis course using rstudio with project-based learning for data science. *2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)*, 581–588. https://doi.org/10.1109/TALE.2018.8615145

Inquirer. (2021). *58% of Filipino students used devices for distance learning – SWS | Inquirer News*. Inquirer.Net. https://newsinfo.inquirer.net/1402235/sws-58-of-pinoy-students-used-devices-for-distance-learning

Kostić, J., & Ranđelović, K. R. (2022). Digital distractions: Learning in multitasking environment. *Psychological Applications and Trends*. https://api.semanticscholar.org/CorpusID:248626251

Kutzhan, A., Shaikym, A., & Sadyk, U. (2023). A comparative study of the impact of electronic devices on university students' academic performance. *2023 17th International Conference on Electronics Computer and Computation (ICECCO)*, 1–4. https://doi.org/10.1109/ICECCO58239.2023.10147158

Lahcene, B. (2015). Control charts for skewed distributions: Johnson's distributions. *International Journal of Statistics in Medical Research*, *4*(2), 217–223. https://doi.org/10.6000/1929-6029.2015.04.02.8

Lai, C.-F., Tsai, C.-W., Chen, S.-Y., Hwang, R.-H., & Yang, C.-S. (2017). An intelligent concept map for e-book via automatic keyword extraction. In T.-T. Wu, R. Gennari, Y.-M. Huang, H. Xie, & Y. Cao (Eds.), *Emerging Technologies for Education* (Vol. 10108, pp. 75–85). Springer International Publishing. https://doi.org/10.1007/978-3-319-52836-6_10

Liaw, A., & Wiener, M. (2002). Classification and regression by randomforest. *R News*, *2*(3), 18–22.

Lu, F., Ferraro, F., & Raff, E. (2022). Continuously generalized ordinal regression for linear and deep models. *Proc. SIAM Int. Conf. Data Min., SDM*, 28–36. Scopus. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85131330370&partnerID=40&md5=1ada1ec867dd5d24d163adef88f5f523

Mafunda, B., & Swart, A. J. (2020). The impact of MindTap on the academic achievement of first-year software application students. *World Transactions on Engineering and Technology Education*, *18*(1), 63–67. Scopus.

Maydeu-Olivares, A., & Cai, L. (2006). A cautionary note on using g^2 (dif) to assess relative model fit in categorical data analysis. *Multivariate Behavioral Research*, *41*(1), 55–64. https://doi.org/10.1207/s15327906mbr4101_4

Mundy, L. K., Canterford, L., Hoq, M., Olds, T., Moreno-Betancur, M., Sawyer, S., Kosola, S., & Patton, G. C. (2020). Electronic media use and academic performance in late childhood: A longitudinal study. *PLOS ONE*, *15*(9), e0237908. https://doi.org/10.1371/journal.pone.0237908

Pinto, M., & Leite, C. (2020). Digital technologies in support of students learning in Higher Education: Literature review. *Digital Education Review*, *37*, 343–360. https://doi.org/10.1344/der.2020.37.343-360

Pirie, W. (2006). Jonckheere tests for ordered alternatives. In S. Kotz, C. B. Read, N. Balakrishnan, & B. Vidakovic (Eds.), *Encyclopedia of Statistical Sciences* (2nd ed.). Wiley. https://doi.org/10.1002/0471667196.ess1311

Pohlert, T. (2024). *PMCMRplus: Calculate pairwise multiple comparisons of mean rank sums extended*. https://CRAN.R-project.org/package=PMCMRplus

Rahali, E. A., Chikhaoui, A., Khattabi, K. E., & Ouzennou, F. (2023). Learning with tablets in the primary school: Learners' perceptions and impact on motivation and academic performance. *International Journal of Information and Education Technology*, *13*(3), 489–495. https://doi.org/10.18178/ijiet.2023.13.3.1830

Ravizza, S. M., Uitvlugt, M. G., & Fenn, K. M. (2017). Logged in and zoned out: How laptop internet use relates to classroom learning. *Psychological Science*, *28*(2), 171–180. https://doi.org/10.1177/0956797616677314

Reinecke, L., Aufenanger, S., Beutel, M. E., Dreier, M., Quiring, O., Stark, B., Wölfling, K., & Müller, K. W. (2017). Digital Stress over the Life Span: The Effects of Communication Load and Internet Multitasking on Perceived Stress and Psychological Health Impairments in a German Probability Sample. *Media Psychology*, *20*(1), 90–115. https://doi.org/10.1080/15213269.2015.1121832

Reisdorf, B. C., Triwibowo, W., & Yankelevich, A. (2020). Laptop or bust: How lack of technology affects student achievement. *American Behavioral Scientist*, *64*(7), 927–949. https://doi.org/10.1177/0002764220919145

Rocha, B., Ferreira, L. I., Martins, C., Santos, R., & Nunes, C. (2023). The Dark Side of Multimedia Devices: Negative Consequences for Socioemotional Development in Early Childhood. *Children*, *10*(11), 1807.

https://doi.org/10.3390/children10111807

Rodríguez-Arelis, G. A., Lourenzutti, R., & Coia, V. (2024). *Lecture 3—Generalized linear models: Ordinal logistic regression—Dsci 562—Regression ii* [Github]. DSCI 562: Regression II. https://ubc-mds.github.io/DSCI_562_regr-2/notes/lecture3_glm_ordinal_regression.html

Sattar Chaudhry, A. (2014). Student response to e-books: Study of attitude toward reading among elementary school children in kuwait. *The Electronic Library*, *32*(4), 458–472. https://doi.org/10.1108/EL-04-2012-0041

Schlegel, B., & Steenbergen, M. (2020). *Brant: Test for parallel regression assumption*. https://CRAN.R-project.org/package=brant

Shejwal, B. R., & Purayidathil, J. (2006). Television viewing of higher secondary students: Does it affect their academic achievement and mathematical reasoning? *Psychology and Developing Societies*, *18*(2), 201–213. https://doi.org/10.1177/097133360601800203

Simon Jackman. (2024). *PSCL: classes and methods for r developed in the political science computational laboratory* (Version 1.5.9.) [R]. https://github.com/atahk/pscl (Original work published 2017)

Supper, W., Talbot, D., & Guay, F. (2022). Association entre le temps d'écoute de la télévision et le rendement scolaire des enfants et des adolescents: Recension systématique et méta-analyse des études longitudinales réalisées à ce jour. *Canadian Journal of Behavioural Science / Revue Canadienne Des Sciences Du Comportement*, *54*(4), 304–314. https://doi.org/10.1037/cbs0000275

Tag, B., Van Berkel, N., Vargo, A. W., Sarsenbayeva, Z., Colasante, T., Wadley, G., Webber, S., Smith, W., Koval, P., Hollenstein, T., Goncalves, J., & Kostakos, V. (2022). Impact of the global pandemic upon young people's use of technology for emotion regulation. *Computers in Human Behavior Reports*, *6*, 100192. https://doi.org/10.1016/j.chbr.2022.100192

Tang, H., & Ji, P. (2014). Using the statistical program r instead of spss to analyze data. In *Tools of Chemistry Education Research* (Vol. 1166, pp. 135–151). American Chemical Society. https://doi.org/10.1021/bk-2014-1166.ch008

Tutz, G., & Berger, M. (2017). Separating location and dispersion in ordinal regression models. *Econometrics and Statistics*, *2*, 131–148. https://doi.org/10.1016/j.ecosta.2016.10.002

Twenge, J. M., Martin, G. N., & Campbell, W. K. (2018). Decreases in psychological well-being among American adolescents after 2012 and links to screen time during the rise of smartphone technology. *Emotion*, *18*(6), 765–780. https://doi.org/10.1037/emo0000403

Venables, W. N., & Ripley, B. D. (2002). *Modern applied statistics with s* (Fourth). Springer. https://www.stats.ox.ac.uk/pub/MASS4/

Wang, F., Ni, X., Zhang, M., & Zhang, J. (2024). Educational digital inequality: A meta-analysis of the relationship between digital device use and academic performance in adolescents. *Computers & Education*, *213*, 105003. https://doi.org/10.1016/j.compedu.2024.105003

Wang, J. C., Hsieh, C.-Y., & Kung, S.-H. (2023). The impact of smartphone use on learning effectiveness: A case study of primary school students. *Education and Information Technologies*, *28*(6), 6287–6320. https://doi.org/10.1007/s10639-022-11430-9

World Bank. (2020). *Philippines Digital Economy Report 2020*. World Bank. https://documents1.worldbank.org/curated/en/796871601650398190/pdf/Philippines-Digital-Economy-Report-2020-A-Better-Normal-Under-COVID-19-Digitalizing-the-Philippine-Economy-Now.pdf

Wrede, S. J. S., Claassen, K., Rodil Dos Anjos, D., Kettschau, J. P., & Broding, H. C. (2023).

Impact of digital stress on negative emotions and physical complaints in the home office: A follow up study. *Health Psychology and Behavioral Medicine*, *11*(1), 2263068. https://doi.org/10.1080/21642850.2023.2263068

Xu, W., Huang, R., Zhang, H., El-Khamra, Y., & Walling, D. (2016). Empowering r with high performance computing resources for big data analytics. In R. Arora (Ed.), *Conquering Big Data with High Performance Computing* (pp. 191–217). Springer International Publishing. https://doi.org/10.1007/978-3-319-33742-5_9

Yee, T., cre, & src), C. M. (LINPACK routines in. (2024). *VGAM: Vector generalized linear and additive models* (Version 1.1-12) [Computer software]. https://cran.r-project.org/web/packages/VGAM/index.html

Yee, T. W. (2022). On the hauck-donner effect in wald tests: Detection, tipping points, and parameter space characterization. *Journal of the American Statistical Association*, *117*(540), 1763–1774. https://doi.org/10.1080/01621459.2021.1886936

Zhou, Y., & Deng, L. (2023). A systematic review of media multitasking in educational contexts: Trends, gaps, and antecedents. *Interactive Learning Environments*, *31*(10), 6279–6294. Scopus. https://doi.org/10.1080/10494820.2022.2032760